E9-252:Mathematical methods and techniques in signal processing HW 4 solutions

Instructor: Shayan G. Srinivasa

Teaching assistants: Ankur Raina and Chaitanya Kumar Matcha

Problem 1

(1)

Without loss of generality we shift the signal to make it causal

$$f(t) = \begin{cases} 3 & -2 \le t < -1 \\ -4 & -1 \le t < 0 \\ 2 & 0 \le t < 1 \\ 1 & 1 \le t < 2 \end{cases}$$
(1)

After shift

$$f(t) = \begin{cases} 3 & 0 \le t < 1\\ -4 & 1 \le t < 2\\ 2 & 2 \le t < 3\\ 1 & 3 \le t < 4 \end{cases}$$
(2)

We project the signal $f(t) = f_0(t)$ onto components lying in V_1 and W_1 because $V_0 = V_1 \oplus W_1$.

$$f(t) = \sum_{n} c_{n}^{(1)} \Phi_{1,n}(t) + \sum_{n} d_{n}^{(1)} \Psi_{1,n}(t)$$

where,

$$\Phi_{j,n}(t) = 2^{-\frac{j}{2}} \Phi(2^{-j} t - n)$$

The components $c_n^{(1)}$ and $d_n^{(1)}$ are obtained by

$$c_n^{(1)} = \langle f_0(t), \Phi_{1,n}(t) \rangle$$
$$d_n^{(1)} = \langle f_0(t), \Psi_{1,n}(t) \rangle$$

Writing $f_0(t) = f_1(t) + g_1(t)$ where, $f_1(t) = \sum_n c_n^{(1)} \Phi_{1,n}(t)$ and $g_1(t) = \sum_n d_n^{(1)} \Psi_{1,n}(t)$. But we can further project the signal $f_1(t)$ lying in V_1 onto components lying in V_2 and W_2 because $V_1 = V_2 \oplus W_2$. Now,

$$f_1(t) = \sum_n c_n^{(2)} \Phi_{2,n}(t) + \sum_n d_n^{(2)} \Psi_{2,n}(t)$$

where,

$$c_n^{(2)} = \langle f_1(t), \Phi_{2,n}(t) \rangle$$
$$d_n^{(2)} = \langle f_1(t), \Psi_{2,n}(t) \rangle$$

Therefore the final wavelet decomposition of the signal is

$$f(t) = \underbrace{\sum_{n} d_{n}^{(1)} \Psi_{1,n}(t)}_{\mathrm{I}} + \underbrace{\sum_{n} c_{n}^{(2)} \Phi_{2,n}(t)}_{\mathrm{II}} + \underbrace{\sum_{n} d_{n}^{(2)} \Psi_{2,n}(t)}_{\mathrm{III}}$$
(3)

The coefficients are found to be

$$c_0^{(1)} = -\frac{1}{\sqrt{2}} \quad c_1^{(1)} = \frac{3}{\sqrt{2}} \quad d_0^{(1)} = \frac{7}{\sqrt{2}} \quad d_1^{(1)} = \frac{1}{\sqrt{2}} \Rightarrow$$
$$f_1(t) = \begin{cases} -0.5 & 0 \le t < 2\\ 1.5 & 2 \le t < 4 \end{cases}$$
(4)

$$g_1(t) = \begin{cases} 3.5 & 0 \le t < 1\\ -3.5 & 1 \le t < 2\\ 0.5 & 2 \le t < 3\\ -0.5 & 3 \le t < 4 \end{cases}$$
(5)

Writing $f_1(t) = f_2(t) + g_2(t)$ where, $f_2(t) = \sum_n c_n^{(2)} \Phi_{2,n}(t)$ and $g_2(t) = \sum_n d_n^{(2)} \Psi_{2,n}(t)$. The coefficients are found to be

$$c_0^{(2)} = 1 \quad d_0^{(2)} = -2 \Rightarrow$$

$$f_2(t) = \begin{cases} 0.5 & 0 \le t < 4 \end{cases}$$
(6)

$$g_2(t) = \begin{cases} -1 & 0 \le t < 2\\ 1 & 2 \le t < 4 \end{cases}$$
(7)

(2)

Frequency response can be plotted for each of the signals namely $f(t), f_1(t), g_1(t), f_2(t), g_2(t)$.



Figure 1: Signal decomposition and Frequency response

(3)

We go from coarser to finer representation of the signal. Terms II and III in (3) represent a coarse representation of the signal. To make the representation finer we add additional information captured in the wavelets $\Psi_{j,n}(t)$. Nulling the last stage would mean equating the coefficient of $\Psi_{2,n}(t)$ to zero. Therefore,

the approximate signal is

$$\begin{split} \widehat{f}(t) &= \sum_{n} d_{n}^{(1)} \Psi_{1,n}(t) + \sum_{n} c_{n}^{(2)} \Phi_{2,n}(t) \\ &= \frac{7}{\sqrt{2}} \Psi_{1,0}(t) + \frac{1}{\sqrt{2}} \Psi_{1,1}(t) + \Phi_{2,0}(t) \\ &= \begin{cases} 4 & 0 \le t < 1 \\ -3 & 1 \le t < 2 \\ 1 & 2 \le t < 3 \\ 0 & 3 \le t < 4. \end{cases} \end{split}$$

Energy lost in the approximation is

$$E_{\text{loss}} = ||f(t) - \hat{f}(t)||^2 = 4.$$

Fraction lost = $\frac{||f(t) - \hat{f}(t)||^2}{||f(t)||^2} = \frac{4}{30}.$

(4)

After performing the wavelet decomposition, we get the wavelet coefficients $d_n^{(1)}, c_n^{(2)}, d_n^{(2)}$. We perform quantization on these coefficients. The quantization is done as follows

$$\Delta = \frac{\max_{n} \{d_{n}^{(1)}, c_{n}^{(2)}, d_{n}^{(2)}\} - \min_{n} \{d_{n}^{(1)}, c_{n}^{(2)}, d_{n}^{(2)}\}}{2^{3}},$$

$$\Delta = \frac{\frac{7}{\sqrt{2}} + 2}{8} = \frac{7\sqrt{2} + 4}{16} = 0.868.$$
Quantization level binary
max=4.95 111
4.076 110
3.208 101

	3.208	101
	2.34	100
	1.472	011
ſ	0.604	010
	-1.132	001
	$\min = -2$	000

We get the new wavelet coefficients namely $\widehat{c}_n^{(j)}, \widehat{d}_n^{(j)}$

$$\hat{d}_0^{(1)} = 4.95 \quad \hat{d}_1^{(1)} = 0.604 \quad \hat{c}_0^{(2)} = 1.472 \quad \hat{d}_0^{(2)} = -2.$$

The binary representation is therefore binary ($\hat{d}_0^{(1)}$)= 111, binary($\hat{d}_1^{(1)}$)= 010, binary($\hat{c}_0^{(2)}$)= 011, binary($\hat{d}_0^{(2)}$)= 000. The reconstructed signal becomes

$$\begin{split} \widehat{f}_q(t) &= \sum_n \widehat{d}_n^{(1)} \Psi_{1,n}(t) + \sum_n \widehat{c}_n^{(2)} \Phi_{2,n}(t) + \sum_n \widehat{d}_n^{(2)} \Psi_{2,n}(t) \\ &= 4.95 \Psi_{1,0}(t) + 0.604 \Psi_{1,1}(t) + 1.472 \Phi_{2,0}(t) - 2 \Psi_{2,0}(t) \end{split}$$

$$\begin{split} E_{\text{qloss}} &= ||f(t) - \hat{f}_q(t)||^2\\ f(t) - \hat{f}_q(t) &= 0.103\Psi_{1,1}(t) - 0.472\Phi_{2,0}(t)\\ \text{Q-Fraction lost} &= \frac{||f(t) - \hat{f}_q(t)||^2}{||f(t)||^2} = \frac{0.232}{30} = 0.7\% \end{split}$$

Note: The translation(time shift) that was done earlier to the signal does not change the quantization and therefore, the quantized signal is time shifted accordingly.

Problem 2

(1)

Calculate the mean vector $\boldsymbol{\mu} = \sum_{i=0}^{6} p_i \boldsymbol{x}_i$ which gives us $\boldsymbol{\mu} = \begin{pmatrix} 0.1875\\ 0.4375 \end{pmatrix}$. Calculate the covariance matrix $\boldsymbol{C} = \sum_{i=0}^{6} p_i (\boldsymbol{x}_i - \boldsymbol{\mu}) (\boldsymbol{x}_i - \boldsymbol{\mu})^T$ which gives

us $\boldsymbol{C} = \begin{pmatrix} 4.4023 & 3.5430 \\ 3.5430 & 4.1211 \end{pmatrix}$.

Lets calculate the eigen vectors of the matrix \boldsymbol{C}

We find the eigen vectors are $\begin{pmatrix} -0.7210 \\ -0.6929 \end{pmatrix}$ and $\begin{pmatrix} 0.6929 \\ -0.7210 \end{pmatrix}$ with corresponding eigen values $\lambda_1 = 7.8075$ and $\lambda_2 = 0.7160$ respectively. Form the matrix $\boldsymbol{\Phi}$ by stacking as columns, the eigen vectors of \boldsymbol{C}

$$\mathbf{\Phi} = \begin{pmatrix} -0.7210 & 0.6929\\ -0.6929 & -0.7210 \end{pmatrix}.$$

The KL representation becomes $\tilde{x}_i = \Phi^T x_i$ giving us the vectors

$$\tilde{x}_{1} = \begin{pmatrix} 0.0280 \\ -1.4139 \end{pmatrix} \tilde{x}_{2} = \begin{pmatrix} -0.6929 \\ -0.7210 \end{pmatrix} \tilde{x}_{3} = \begin{pmatrix} 4.2418 \\ 0.0841 \end{pmatrix} \\ \tilde{x}_{4} = \begin{pmatrix} -0.7210 \\ 0.6929 \end{pmatrix} \tilde{x}_{5} = \begin{pmatrix} -0.0280 \\ 1.4139 \end{pmatrix} \tilde{x}_{6} = \begin{pmatrix} -4.2418 \\ -0.0841 \end{pmatrix}$$

(2)

New representation keeping only the dominant eigen component is done by taking inner product of the dominant eigen vector namely $\hat{e} = \begin{pmatrix} -0.7210 \\ -0.6929 \end{pmatrix}$

$$\widehat{x_{i}} = \langle x_{i}, \widehat{e}
angle \, \widehat{e}$$

This gives us

$$\widehat{x}_{1} = \begin{pmatrix} -0.202 \\ -0.0194 \end{pmatrix} \widehat{x}_{2} = \begin{pmatrix} 0.4996 \\ 0.4802 \end{pmatrix} \widehat{x}_{3} = \begin{pmatrix} -3.0583 \\ -2.9393 \end{pmatrix}$$
$$\widehat{x}_{4} = \begin{pmatrix} 0.5198 \\ 0.4996 \end{pmatrix} \widehat{x}_{5} = \begin{pmatrix} 0.202 \\ 0.0194 \end{pmatrix} \widehat{x}_{6} = \begin{pmatrix} 3.0583 \\ 2.9393 \end{pmatrix}.$$

All points point in the direction of \hat{e} .

All the points lie on the straight line y = 0.9610x. Fraction of the signal energy lost is $\frac{\lambda_2}{\lambda_1 + \lambda_2} = 8.4\%$ (3)

Let the equation of the straight line that minimizes the squared distance from the original points be y = mx + c. We need to evaluate the optimal m and c. The cost function that needs to be minimized is $\mathcal{E} = \sum_{i=0}^{6} p_i (mx_i + c - y_i)^2$, where x_i and y_i refer to the first and second components of x_i respectively.

$$\frac{\partial \mathcal{E}}{\partial m} = 0 \quad \& \quad \frac{\partial \mathcal{E}}{\partial c} = 0 \Rightarrow$$

$$71m + 3c = 58 \quad \& \quad 3m + 16c = 7 \Rightarrow$$

$$m = 0.8048 \quad \& \quad c = 0.2866$$

(4)

After dimensionality reduction, the points lie on a straight line y = 0.9610x. The optimal line that separates the reduced points must be perpendicular to the straight line y = 0.9610x. Let the equation of the straight line that minimizes the squared distance from the points after dimensionality reduction be

0.9610y + x = c. We need to evaluate the optimal c. The cost function that needs to be minimized is $\widehat{\mathcal{E}} = \sum_{i=0}^{6} p_i (0.9610y_i + x_i - c)^2$, where x_i and y_i refer to the first and second components of $\widehat{x_i}$ respectively.

$$\frac{\partial \widehat{\mathcal{E}}}{\partial c} = 0 \Rightarrow$$
$$16c = 11.7660 \Rightarrow c = 0.7354$$