

TTT4120 Digital Signal Processing Solutions for Problem Set 7

Problem 1:

(a).

The samples from the white noises are uncorrelated and drawn from the corresponding distribution. Since a white noise has zero mean and we are told that these noises have unit variance, we have all the parameters for their probability distributions. For the uniform distribution we have to find the limits (which will be symmetric because of the zero mean property):

$$\frac{1}{2a} \int_{-a}^{a} x^2 dx = 1 \ \to a = \sqrt{3} \,,$$

Matlab code:

g = randn(1,N); % gaussian
u = sqrt(3)*(2*rand(1,N) - 1); % uniform
b = 2*(rand(1,N)>0.5)-1; % binary

Fig.1 shows the realization of the different white noises. It is common for all the noises that the samples are uncorrelated for each of them. This means that given one sample there is no information about the value of the next one. The binary noise is limited to two different values, whereas the uniform and the gaussian noise takes values in a given interval. At first sight it is difficult to make difference between the gaussian noise and the uniform one. However it can be seen that the gaussian noise takes some values out of $(-\sqrt{3},\sqrt{3})$. In addition, the value of the samples from the gaussian noise are concentrated in the center, where as the value of the samples of the uniform noise are equally spaced.

(b).

White binary noise:

$$P_X(x) = \begin{cases} 0.5 & \text{if } x = \pm 1\\ 0 & \text{otherwise} \end{cases}$$

White uniform noise:

$$P_X(x) = \begin{cases} \frac{1}{2\sqrt{3}} & \text{if } x \in (-\sqrt{3}, \sqrt{3}) \\ 0 & \text{otherwise} \end{cases}$$

White gaussian noise:

$$P_X(x) = \frac{1}{\sqrt{2\pi}}e^{-\frac{x^2}{2}}$$

To compute the mean of X(n) we use the symmetry properties of $P_X(x)$:

$$\int x P_X(x) dx = 0$$

To compute the autocorrelation function we have to use the fact that the sample are uncorrelated (because they are white signals):

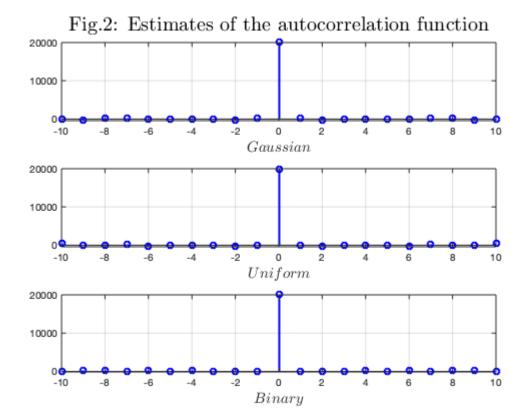
$$R_X[k] = EX[n]X[n-k] = \sigma^2\delta(k)$$

The power density spectrum in the DTFT of the autocorrelation function:

$$S_X(w) = DTFT\{R_X[k]\} = \sigma_X^2$$

(c).

The mean estimates should be quite accurate (less than 0.001% error). Fig.2 shows that the estimated correlations are very accurate. They were found using the function xcorr so that we get a normalized estimate.



Problem 2:

The mean value of the input w[n] is zero, because it is a white noise process. The autocorrelation function of the input, w[n], is given by

$$\gamma_{ww}[m] = E\{w[n]w[n+m]\} = \sigma_w^2 \delta[m] = \frac{3}{4}\delta[m],$$

since the samples of white noise are uncorrelated. The power density spectrum of the input is given by

$$\Gamma_{ww}(f) = DTFT\{\gamma_{ww}[m]\} = \sum_{m=-\infty}^{\infty} \gamma_{ww}[m]e^{-j2\pi f m} = \sum_{m=-\infty}^{\infty} \sigma_w^2 \delta[m]e^{-j2\pi f m} = \sigma_w^2 = \frac{3}{4}$$

(a).

The mean of the signal x(n) is given by

$$m_x = E\{x[n]\} = m_w \sum_{k=-\infty}^{\infty} h[k] = 0$$
, since $m_w = 0$.

The autocorrelation function of the signal x(n) is given by

$$\gamma_{xx}[m] = \gamma_{ww}[m] * r_{hh}[m],$$

where $r_{hh}[m]$ is the autocorrelation function of the unit sample response h[n] of the filter (which is a deterministic signal), i.e.

$$r_{hh}[m] = \sum_{n=-\infty}^{\infty} h[n]h[n+m]$$

The unit sample response for the filter is given by

$$h(n) = \mathcal{Z}^{-1}\left\{H(z)\right\} = \left(-\frac{1}{2}\right)^n u(n).$$

We first find the autocorrelation function $r_{hh}[m]$ for $m \ge 0$,

$$r_{hh}[m] = \sum_{n=-\infty}^{\infty} \left(-\frac{1}{2}\right)^n u[n] \left(-\frac{1}{2}\right)^{n+m} u[n+m] = \sum_{n=0}^{\infty} \left(-\frac{1}{2}\right)^{2n+m}$$
$$= \left(-\frac{1}{2}\right)^m \sum_{n=0}^{\infty} \left(-\frac{1}{4}\right)^n = \left(-\frac{1}{2}\right)^m \frac{1}{1-\frac{1}{4}} = \frac{4}{3} \left(-\frac{1}{2}\right)^m$$

For m < 0, we have that $r_{hh}[m] = r_{hh}[-m] = \frac{4}{3} \left(-\frac{1}{2}\right)^{-m}$. It follows that

$$r_{hh}[m] = \frac{4}{3} \left(-\frac{1}{2} \right)^{|m|}$$
, for all m

The autocorrelation function of the signal x[n] is now given by

$$\gamma_{xx}[m] = \gamma_{ww}[m] * r_{hh}[m] = \frac{3}{4}\delta[m] * \frac{4}{3}\left(-\frac{1}{2}\right)^{|m|} = \left(-\frac{1}{2}\right)^{|m|}.$$

The power density spectrum of the signal x(n) is given by

$$\Gamma_{xx}(\omega) = \Gamma_{ww}(\omega) |H(\omega)|^2$$

We can compute $|H(\omega)|^2$ from the transfer function H(z) by remembering that $H(\omega) = H(z)\big|_{z=e^{j\omega}}$

$$|H(\omega)|^2 = H(\omega)H^*(\omega) = \frac{1}{1 + \frac{1}{2}e^{-j\omega}} \cdot \frac{1}{1 + \frac{1}{2}e^{j\omega}} = \frac{4}{5 + 4\cos\omega}.$$

It follows that

$$\Gamma_{xx}(\omega) = \frac{3}{4} \frac{4}{5 + 4\cos\omega} = \frac{3}{5 + 4\cos\omega}.$$

The power of the signal x(n) is given by

$$P_x = E\{x^2[n]\} = \gamma_{xx}(0) = 1,$$

and variance

$$\sigma_x^2 = E\{(x[n] - m_x)^2\} = E\{x[n]^2\} = P_x = 1$$
, since $m_x = 0$

(b).

We have the following expressions for the estimates:

Mean:

$$\hat{m}_x = \frac{1}{N} \sum_{n=0}^{N-1} x[n]$$

Power:

$$\hat{P}_x = \frac{1}{N} \sum_{n=0}^{N-1} x^2 [n]$$

Autocorrelation function:

$$\widehat{\gamma}_{xx}[l] = \begin{cases} \frac{1}{N} \sum_{n=0}^{N-1} x[n]x[n+l] & \text{for } 0 \le |l| \le N-1 \\ 0 & \text{for } N \le |l| \end{cases}$$

· Power spectral density:

$$\widehat{\Gamma}_{xx} = \mathrm{DFT}(\widehat{\gamma}_{xx}[l])$$

(c).

The signal x[n] can be estimated by first generating a segment of white Gaussian noise using the Matlab command randn, and then filtering it trough the filter H(z) using Matlab command filter. The plots of $\gamma_{xx}[m]$, $\widehat{\gamma}_{xx}[m]$, $\Gamma_{xx}(\omega)$, and $\widehat{\Gamma}_{xx}(\omega)$ and are shown in Fig.3.

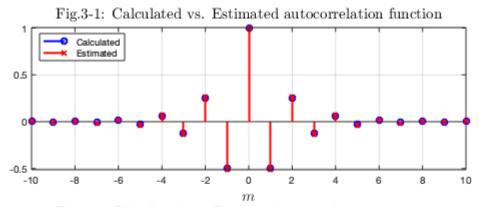


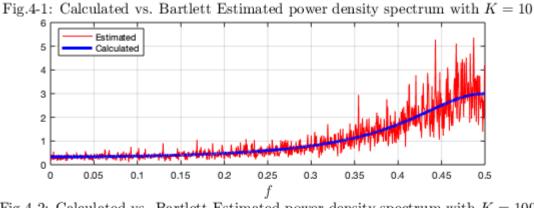
Fig. 3-2: Calculated vs. Estimated power density spectrum

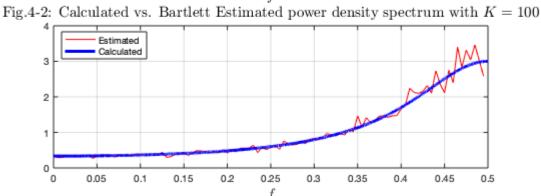
Estimated Calculated

Calculated

0 0.05 0.1 0.15 0.2 0.25 0.3 0.35 0.4 0.45 0.5

(d). The Bartlett estimation of the power density spectrum is represented in Fig.4 for virious value of K.





Problem 3:

The histograms for K=20,40 and 100 are shown in Fig.5. We observe that the variance of the mean estimate is reduced when the segment length is increased. This is confirmed when the variances is computed using Matlab command var.

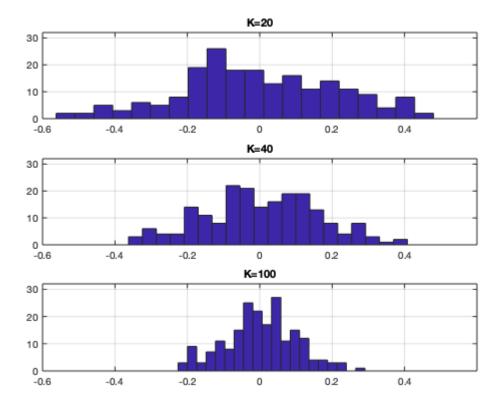


Fig.5: Histograms of the mean value computed on segments of length $\,20,40\,$ and $\,100\,$