

EE608 Adaptive Signal Processing

Problem Set 2

1) Computing the Sample Covariance Matrix

Let $Y(k)$ be a discrete time stochastic process, and $\{y(k)\}_0^{N-1}$ be a realization of this process. A typical problem in practice is to compute the second order statistics of the process.

The procedure for computing the mean is well known; in fact it is the answer obtained earlier using the maximum likelihood estimation procedure under Gaussian assumption, namely

$$\hat{m}_N = \frac{1}{N} \sum_0^{N-1} Y(k)$$

To avoid a new notation we use the *computer programming definition*

$$Y(k) := Y(k) - \hat{m}_N \rightarrow y(k) := y(k) - \hat{m}_N$$

Now we look for procedures for computing the covariance of $Y(k)$ using $\{y(k)\}_0^{N-1}$.

(a) Let

$$\bar{r}_N(k) = \frac{1}{N-k} \left[\sum_{j=0}^{N-k-1} y(j+k)y(j) \right], k = 0, 1, \dots, N-1$$

show that

- i. $\bar{r}_N(k)$ is an unbiased estimate of the true covariance parameter $r(k) = E[(j+k)Y(j)]$
- ii. the covariance matrix constructed using $r_N(k)$ will not be non-negative definite. Because of this problem one looks for alternative methods for computing the sample covariance matrix.

(b) Alternately let the sample covariance matrix be defined as

$$r_N(k) = \frac{1}{N-k} \left[\sum_{j=0}^{N-k-1} y(j+k)y(j) \right], k = 0, 1, \dots, N-1$$

- i. Show that $r_N(k)$ is not an unbiased estimate of the true covariance parameter; nevertheless it is an asymptotically unbiased estimate.
- ii. Show that the covariance matrix constructed using $\bar{r}_N(k)$ is non-negative definite.
(Hint: Express the sample covariance matrix as a product of data matrix with its transpose).

2) Let $x(\cdot)$ and $y(\cdot)$ be discrete time, jointly stationary zero mean processes with $E[x(n)y(m)] = r_{xy}(n-m)$, $E[y(n)y(m)] = r_{yy}(n-m)$ Show that the parameters involved in computing the following linear least-squares estimates are identical.

(a) $\hat{E}[x(n)|y(n-1), \dots, y(n-M)]$

(b) $\hat{E}[x(n+N)|y(n+N-1), \dots, y(n+N-M)]$

Note: This simple result shall be used often.

3) Determining $\hat{x}(k|n)$ using Levinson's Algorithm

In class we developed the Levinson's Algorithm for the one step prediction problem and for generating the innovations. In this problem you are required to develop a recursive scheme for computing $\hat{x}(k|n)$ in the framework of Levinson's algorithm.

Show that

$$\hat{x}(k|n+1) = \hat{x}(k|n) + \Gamma(k, n)\epsilon(n)$$

Determine the expression for the gain $\Gamma(k, n)$ and an expression for recursively computing it. The above is referred to as the measurement update equation.

4) In the Levinson Algorithm derive the expression

$$p(n) = r(0) + \sum_{i=0}^{n-1} a_n(n-i)r(i-n)$$

where $p(n)$ is the innovations (error) variance

$$p(n) = E[\{y(n) - \hat{y}(n|n-1)\}^2]$$

5) Let $y(\cdot)$ be a zero mean process with

$$E[y(k+m)y(m)] = \left(\frac{1}{4}\right)^{|k|}$$

and $x(\cdot)$ be another process with

$$E[y(k+m)y(m)] = \begin{cases} (2/3)^k & k \geq 0 \\ (1/3)^k & k \leq 0 \end{cases}$$

$$E[x(k+m)x(m)] = \left(\frac{1}{2}\right)^{|k|}$$

(a) Find the optimal filter for computing the linear least squares estimate of $x(n+N)$, $N > 0$, based on $\{y(k), k \leq n\}$.

6) **Simulation:** Consider the sample values of a stationary process $y(\cdot)$ on the home page for the **ASP course**: in <http://sharada.ee.iitb.ac.in/ee608/>, file name is levinson.dat

(a) Determine the first 50 covariance lags $r(n)$ $0 \leq n \leq 50$.

(b) Using Levinson's algorithm determine an appropriate AR model. Comment on the goodness of this model. If there are any deficiencies or problems give reasons for them.