ECE 830 Fall 2011 Statistical Signal Processing instructor: R. Nowak

Lecture 8: Signal Detection and Noise Assumption

# **1** Signal Detection

$$H_0: X = W$$
  
$$H_1: X = S + W$$

where  $W \sim N(0, \sigma^2 I_{n \times n})$  and  $S = [s_1, s_2, \dots, s_n]^T$  is the known signal waveform.

$$P_0(X) = \frac{1}{(2\pi\sigma^2)^{\frac{n}{2}}} exp(-\frac{1}{2\sigma^2}X^T X)$$
  

$$P_1(X) = \frac{1}{(2\pi\sigma^2)^{\frac{n}{2}}} exp[-\frac{1}{2\sigma^2}(X-S)^T(X-S)]$$

The second equation holds because under hypothesis  $H_0$ , W = X - S.

The Log Likelihood Ratio test is

$$\log \Lambda(x) = \log \frac{P_W(X)}{P_W(X-S)} = -\frac{1}{2\sigma^2} [(X-S)^T (X-S) - X^T X] = -\frac{1}{2\sigma^2} [-2X^T + S^T S] \overset{H_1}{\underset{H_0}{\gtrless}} \gamma' S = -\frac{1}{2\sigma^2} [-2X^T + S^T S] \overset{H_1}{\underset{H_0}{\gtrless}} \gamma' S = -\frac{1}{2\sigma^2} [-2X^T + S^T S] \overset{H_1}{\underset{H_0}{\gtrless}} \gamma' S = -\frac{1}{2\sigma^2} [-2X^T + S^T S] \overset{H_1}{\underset{H_0}{\gtrless}} \gamma' S = -\frac{1}{2\sigma^2} [-2X^T + S^T S] \overset{H_1}{\underset{H_0}{8}} \gamma' S = -\frac{1}{2\sigma^2} [-2X^T + S^T S] \overset{H_1}{\underset{H_0}{8}} \gamma' S = -\frac{1}{2\sigma^2} [-2X^T + S^T S] \overset{H_1}{\underset{H_0}{8}} \gamma' S = -\frac{1}{2\sigma^2} [-2X^T + S^T S] \overset{H_1}{\underset{H_0}{8}} \gamma' S = -\frac{1}{2\sigma^2} [-2X^T + S^T S] \overset{H_1}{\underset{H_0}{8}} \gamma' S = -\frac{1}{2\sigma^2} [-2X^T + S^T S] \overset{H_1}{\underset{H_0}{8}} \gamma' S = -\frac{1}{2\sigma^2} [-2X^T + S^T S] \overset{H_1}{\underset{H_0}{8}} \gamma' S = -\frac{1}{2\sigma^2} [-2X^T + S^T S] \overset{H_1}{\underset{H_0}{8}} \gamma' S = -\frac{1}{2\sigma^2} [-2X^T + S^T S] \overset{H_1}{\underset{H_0}{8}} \gamma' S = -\frac{1}{2\sigma^2} [-2X^T + S^T S] \overset{H_1}{\underset{H_0}{8}} \gamma' S = -\frac{1}{2\sigma^2} [-2X^T + S^T S] \overset{H_1}{\underset{H_0}{8}} \gamma' S = -\frac{1}{2\sigma^2} [-2X^T + S^T S] \overset{H_1}{\underset{H_0}{8}} \gamma' S = -\frac{1}{2\sigma^2} [-2X^T + S^T S] \overset{H_1}{\underset{H_0}{8}} \gamma' S = -\frac{1}{2\sigma^2} [-2X^T + S^T S] \overset{H_1}{\underset{H_0}{8}} \gamma' S = -\frac{1}{2\sigma^2} [-2X^T + S^T S] \overset{H_1}{\underset{H_0}{8}} \gamma' S = -\frac{1}{2\sigma^2} [-2X^T + S^T S] \overset{H_1}{\underset{H_0}{8}} \gamma' S = -\frac{1}{2\sigma^2} [-2X^T + S^T S] \overset{H_1}{\underset{H_0}{8}} \gamma' S = -\frac{1}{2\sigma^2} [-2X^T + S^T S] \overset{H_1}{\underset{H_0}{8}} \gamma' S = -\frac{1}{2\sigma^2} [-2X^T + S^T S] \overset{H_1}{\underset{H_0}{8}} \gamma' S = -\frac{1}{2\sigma^2} [-2X^T + S^T S] \overset{H_1}{\underset{H_0}{8}} \gamma' S = -\frac{1}{2\sigma^2} [-2X^T + S^T S] \overset{H_1}{\underset{H_0}{8}} \gamma' S = -\frac{1}{2\sigma^2} [-2X^T + S^T S] \overset{H_1}{\underset{H_0}{8}} \gamma' S = -\frac{1}{2\sigma^2} [-2X^T + S^T S] \overset{H_1}{\underset{H_0}{8}} \gamma' S = -\frac{1}{2\sigma^2} [-2X^T + S^T S] \overset{H_1}{\underset{H_0}{8}} \gamma' S = -\frac{1}{2\sigma^2} [-2X^T + S^T S] \overset{H_1}{\underset{H_0}{8}} \gamma' S = -\frac{1}{2\sigma^2} [-2X^T + S^T S] \overset{H_1}{\underset{H_0}{8}} \gamma' S = -\frac{1}{2\sigma^2} [-2X^T + S^T S] \overset{H_1}{\underset{H_0}{8}} \gamma' S = -\frac{1}{2\sigma^2} [-2X^T + S^T S] \overset{H_1}{\underset{H_0}{8}} \gamma' S = -\frac{1}{2\sigma^2} [-2X^T + S^T S] \overset{H_1}{\underset{H_0}{8}} \gamma' S = -\frac{1}{2\sigma^2} [-2X^T + S^T S] \overset{H_1}{\underset{H_0}{8}} \gamma' S = -\frac{1}{2\sigma^2} [-2X^T + S^T S] \overset{H_1}{\underset{H_0}{8}} \gamma' S = -\frac{1}{2\sigma^2} [-2X^T + S^T S] \overset{H_1}{\underset{H_0}{8}} \gamma' S = -\frac{1}{2\sigma^2} [-2X^T + S^T + S^T ] \overset{H_1}{\underset{H_0}{8}} \gamma' S = -\frac{1}{2$$

After simplifying it, we can get

$$X^T S \underset{H_0}{\overset{H_1}{\gtrless}} \sigma^2 \gamma' + \frac{S^T S}{2} = \gamma$$

In this case,  $X^T S$  is the sufficient statistics t(x) for the parameter  $\theta = 0, 1$ . Note that  $S^T S = ||S||_2^2$  is the signal energy. The LR detector "filters" data by projecting them onto signal subspace.

## 1.1 Example 1

Suppose we want to control the probability of false alarm. For example, choose  $\gamma$  so that  $\mathbb{P}(X^T S > \gamma \mid H_0) \leq 0.05$ .

The test statistic  $X^T S$  is usually called "matched filter".

In particular, projection onto subspace spanned by S is

$$P_S = \frac{SS^T}{S^TS} = \frac{S}{\|S\|} \cdot \frac{S^T}{\|S\|}$$
$$P_S X = \frac{SS^T}{\|S\|^2} X = (X^T S) \frac{S}{\|S\|^2}$$



Figure 1: Projection of X onto subspace S

where  $\frac{X^T S}{\|S\|^2}$  is just a number.

Geometrically, suppose the horizontal line is the subspace S and X is some other vector. The projection of vector X into subspace S can be expressed in the figure 1.

### 1.2 Example 2

Suppose the signal value  $S_k$  is sinusoid.

$$S_k = \cos(2\pi f_0 k + \theta), k = 1, \dots, n$$

The match filter in this case is to compute the value in the specific frequency. So  $P_S$  in this example is a bandpass filter.

## **1.3** Performance Analysis

Next problem what we want to know is what's the probability density of  $X^T S$ , which is the sufficient statistics of this test.

$$\begin{array}{rcl} H_0: \ X & \sim & N(0,\sigma^2 I) \\ H_1: \ X & \sim & N(S,\sigma^2 I) \end{array}$$

 $X^T S = \sum_{k=1}^n X_k S_k$  is also Gaussian distributed. Recall if  $X \sim N(\mu, \Sigma)$ , then  $Y = AX \sim N(A\mu, A\Sigma A^T)$ , where A is a matrix.

Since  $Y = X^T S = S^T X$ , Y is a scalar. So we can get

$$H_0: X^T S \sim N(0^T S, S^T \sigma^2 IS) = N(0, \sigma^2 ||S||^2)$$
  

$$H_1: X^T S \sim N(S^T S, S^T \sigma^2 IS) = N(||S||^2, \sigma^2 ||S||^2)$$

The probability of false alarm is  $P_{FA} = Q(\frac{\gamma - 0}{\sigma \|S\|})$ , and the probability of detection is  $P_D = Q(\frac{\gamma - \|S\|^2}{\sigma \|S\|}) = Q(\frac{\gamma}{\sigma \|S\|} - \frac{\|S\|}{\sigma})$ . Since Q function is invertible, we can get  $\frac{\gamma}{\sigma \|S\|} = Q^{-1}(P_{FA})$ . Therefore,  $P_D = Q(Q^{-1}(P_{FA}) - \frac{\|S\|}{\sigma})$ . In the equation,  $\frac{\|S\|}{\sigma}$  is the square root of Signal Noise Ratio( $\sqrt{SNR}$ ).

## 2 AWGN Assumption

Is real-world noise really additive, white and Gaussian? Well, here are a few observations. Noise in many applications (e.g. communication and radar) arose from several independent sources, all adding together



Figure 2: Distribution of  $P_0$  and  $P_1$ 



Figure 3: Relation between probability of detection and false alarm

at sensors and combining additively to the measurement. AWGN is gaussian distributed as the following formula.

$$W \sim N(0, \sigma^2 I)$$

**CLT(Central Limit Theorem):** If  $x_1, \ldots, x_n$  are independent random variables with means  $\mu_i$  and variances  $\sigma_i^2 < \infty$ , then  $Z_n = \frac{1}{\sqrt{n}} \sum_{i=1}^n \frac{x_i - \mu_i}{\sigma_i} \to N(0, 1)$  in distribution quite quickly. Thus, it is quite reasonable to model noise as additive and Gaussian list in many applications. However,

whiteness is not always a good assumption.

#### 2.1Example 3

Suppose  $W = S_1 + S_2 + \cdots + S_k$ , where  $S_1, S_2, \ldots, S_k$  are inteferencing signals that are not of interest. But each of them is structured/correlated in time. Therefore, we need a more generalized form of noise, which is "Colored Gaussian Noise".

### **Colored Gaussian Noise** 3

 $W \sim N(0, \Sigma)$  is called correlated or "colored" noise, where  $\Sigma$  is a structured covariance matrix. Consider the binary hypothesis test in this case.



Figure 4: Relation between probability of detection and SNR

$$H_0: X = S_0 + W$$
  
$$H_1: X = S_1 + W$$

where  $W \sim N(0, \Sigma)$  and  $S_0$  and  $S_1$  are know signal waveforms. So we can rewrite the hypothesis as

$$H_0: X \sim N(S_0, \Sigma)$$
$$H_1: X \sim N(S_1, \Sigma)$$

The probability density of each hypothesis is

$$P_i(X) = \frac{1}{(2\pi)^{\frac{2}{n}} (\Sigma)^{\frac{1}{2}}} exp[-\frac{1}{2}(X - S_i)^T \Sigma^{-1} (X - S_i)], i = 0, 1$$

The log likelihood ratio is

$$\log(\frac{P_1(X)}{P_2(X)}) = -\frac{1}{2}[(X-S_1)^T \Sigma (X-S_1) - (X-S_0)^T \Sigma^{-1} (X-S_0)] = X^T \Sigma^{-1} (S_1-S_0) - \frac{1}{2} S_1^T \Sigma^{-1} S_1 + \frac{1}{2} S_0^T \Sigma^{-1} S_0 \overset{H_1}{\underset{H_0}{\gtrless}} \gamma' \\ (S_1 - S_0) \Sigma^{-1} X \overset{H_1}{\underset{H_0}{\gtrless}} \gamma' + \frac{S_1^T \Sigma^{-1} S_1}{2} - \frac{S_0^T \Sigma^{-1} S_0}{2} = \gamma$$

Let  $t(X) = (S_1 - S_0)\Sigma^{-1}X$ , we can get

$$H_0: t \sim N((S_1 - S_0)\Sigma^{-1}S_0, (S_1 - S_0)^T\Sigma^{-1}(S_1 - S_0))$$
  
$$H_1: t \sim N((S_1 - S_0)\Sigma^{-1}S_1, (S_1 - S_0)^T\Sigma^{-1}(S_1 - S_0))$$

The probability of false alarm is

$$P_{FA} = Q\left(\frac{\gamma - (S_1 - S_0)^T \Sigma^{-1} S_0}{[(S_1 - S_0)^T \Sigma^{-1} (S_1 - S_0)]^{\frac{1}{2}}}\right)$$

In this case it is natural to define

$$SNR = (S_1 - S_0)^T \Sigma^{-1} (S_1 - S_0)$$

# 3.1 Example 4

$$\begin{split} S_1 = [\frac{1}{2}, \frac{1}{2}], \, S_0 = [-\frac{1}{2}, -\frac{1}{2}], \, \Sigma = \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix}, \, \Sigma^{-1} = \frac{1}{1-\rho^2} \begin{bmatrix} 1 & -\rho \\ -\rho & 1 \end{bmatrix}. \end{split}$$
 The test statistics is

$$y = (S_1 - S_0)\Sigma^{-1}X = [1, 1]\frac{1}{1 - \rho^2} \begin{bmatrix} 1 & -\rho \\ -\rho & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \frac{1}{1 + \rho}(x_1 + x_2)$$

$$H_0: \ y \sim N(-\frac{1}{1+\rho}, \frac{2}{1+\rho})$$
$$H_1: \ y \sim N(+\frac{1}{1+\rho}, \frac{2}{1+\rho})$$

The probability of false alarm is

$$P_{FA} = Q(\frac{\gamma + \frac{1}{1+\rho}}{\sqrt{\frac{2}{1+\rho}}})$$

The probability of detection is

$$P_D = Q(\frac{\gamma - \frac{1}{1+\rho}}{\sqrt{\frac{2}{1+\rho}}})$$



Figure 5: ROC curve at different  $\rho$