

# ECE531 Screencast 10.3: Binary Detection in Additive Correlated Gaussian Noise

D. Richard Brown III

Worcester Polytechnic Institute

# Binary Detection in Correlated Noise

Problem setup:

- ▶ We have two known discrete-time signals  $s_0, s_1 \in \mathbb{R}^n$  that are observed in additive white Gaussian noise.
- ▶ A signal  $x \in \{s_0, s_1\}$  is transmitted and we observe a realization  $y \in \mathbb{R}^n$  of the random variable

$$Y = x + W$$

where  $W \sim \mathcal{N}(0, \Sigma)$  is zero mean-additive Gaussian noise.

- ▶ The positive definite noise covariance matrix  $\Sigma$  is defined as

$$\Sigma = \mathbb{E}[WW^T]$$

- ▶ We assume that the receiver knows the noise distribution  $\mathcal{N}(0, \Sigma)$ .
- ▶ Given the observation  $y$ , we must decide whether  $s_0$  or  $s_1$  was transmitted.
- ▶ Like the case with AWGN, this is a simple binary HT problem.

## Likelihood Ratio

$$\begin{aligned}
 L(\mathbf{y}) &= \frac{p_1(\mathbf{y})}{p_0(\mathbf{y})} \\
 &= \exp\left(\frac{(\mathbf{y} - \mathbf{s}_0)^\top \Sigma^{-1}(\mathbf{y} - \mathbf{s}_0) - (\mathbf{y} - \mathbf{s}_1)^\top \Sigma^{-1}(\mathbf{y} - \mathbf{s}_1)}{2}\right)
 \end{aligned}$$

Converting to a log-likelihood ratio, we can write

$$\begin{aligned}
 \ell(\mathbf{y}) &:= 2 \ln(L(\mathbf{y})) \\
 &= (\mathbf{y} - \mathbf{s}_0)^\top \Sigma^{-1}(\mathbf{y} - \mathbf{s}_0) - (\mathbf{y} - \mathbf{s}_1)^\top \Sigma^{-1}(\mathbf{y} - \mathbf{s}_1)
 \end{aligned}$$

The decision rule template is similar to the AWGN case:

$$\rho(\mathbf{y}) = \begin{cases} 1 & \text{if } \ell(\mathbf{y}) \geq 2 \ln v \\ 0 & \text{if } \ell(\mathbf{y}) < 2 \ln v \end{cases}$$

# Decorrelation

## Lemma

A real symmetric matrix  $P$  is positive definite if and only if there exists a nonsingular matrix  $S$  such that  $P = S^T S$ .

Given  $P$ , how can we find  $S$  such that  $P = S^T S$ ?

**Cholesky factorization** (see Matlab function `chol`).

Since  $\Sigma$  is positive definite, then so is  $\Sigma^{-1}$ . Hence, we can write

$$\Sigma^{-1} = S^T S$$

where  $S$  is invertible. Now let

$$\begin{aligned} \bar{y} &= Sy \\ &= S(x + w) \\ &= \begin{cases} \bar{s}_0 + \bar{w} & \text{if } x = s_0 \\ \bar{s}_1 + \bar{w} & \text{if } x = s_1 \end{cases} \end{aligned}$$

# Decorrelation

Note that  $S$  just specifies a one-to-one coordinate transformation between  $\mathbb{R}^n$  and  $\mathbb{R}^n$ . In this new coordinate system

$$\begin{aligned}
 (y - s_j)^\top \Sigma^{-1} (y - s_j) &= (y - s_j)^\top S^\top S (y - s_j) \\
 &= [S(y - s_j)]^\top S(y - s_j) \\
 &= (\bar{y} - \bar{s}_j)^\top (\bar{y} - \bar{s}_j) \\
 &= \|\bar{y} - \bar{s}_j\|^2
 \end{aligned}$$

The noise is still Gaussian after this transformation, of course, with

$$\begin{aligned}
 \mathbb{E}[\bar{W}] &= \mathbb{E}[SW] = 0 \\
 \mathbb{E}[\bar{W}\bar{W}^\top] &= \mathbb{E}[SWW^\top S^\top] = S\mathbb{E}[WW^\top]S^\top = S\Sigma S^\top = I
 \end{aligned}$$

Hence, the coordinate transformation has decorrelated (whitened) the noise. After this decorrelation operation, we can just use our prior results for binary detection in AWGN.

# Neyman-Pearson and Bayes Decision Rules

In both cases, the decision rule is of the form (with  $\bar{z} = (\bar{s}_1 - \bar{s}_0)^\top \bar{y}$ )

$$\rho(y) = \begin{cases} 1 & \bar{z} \geq v' \\ 0 & < \end{cases}$$

**Neyman-Pearson:** A false positive occurs if  $x = s_0$  and  $\bar{Z} \geq v'$ . Given  $x = s_0$ , the decision variable  $\bar{Z} \sim \mathcal{N}(\bar{s}^\top \bar{s}_0, \|\bar{s}\|^2)$ . Hence

$$P_{\text{fp}} = Q\left(\frac{v' - \bar{s}^\top \bar{s}_0}{\|\bar{s}\|}\right) \leq \alpha$$

Setting this equal to  $\alpha$  yields  $v' = \|\bar{s}\|Q^{-1}(\alpha) + \bar{s}^\top \bar{s}_0$ . The probability of detection is then  $P_D = Q\left(\frac{v' - \bar{s}^\top \bar{s}_1}{\sigma\|\bar{s}\|}\right)$ .

**Bayes:** The Bayes detector requires the specification of a prior  $\pi_0$  and a cost matrix  $C$ . The decision threshold is  $v' = \ln \tau + \frac{1}{2}(\|\bar{s}_1\|^2 - \|\bar{s}_0\|^2)$  with

$$\tau := \frac{\pi_0(C_{10} - C_{00})}{\pi_1(C_{01} - C_{11})}.$$