Deterministic Signals (Bayesian Approach)

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Introduction

ullet Recall detection of a known signal s_j in noise studied previously

$$H_0: \quad x_j = \xi_j$$

$$H_1: \quad x_j = s_j + \xi_j$$

- \bullet We now extend to the binary case of two signals $s_j^{(0)}$ and $s_j^{(1)}$
- The detection problem is now a classification problem

$$H_0: x_j = s_j^{(0)} + \xi_j$$

$$H_1: x_j = s_j^{(1)} + \xi_j$$

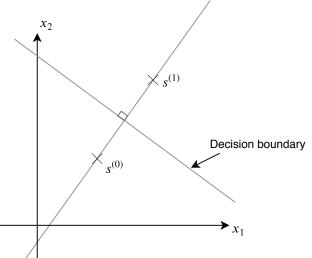
• $\xi_j \sim \mathcal{N}(0,\sigma^2)$, all errors have the same cost, no gains, and equal priors \Rightarrow ML detector:

$$\frac{p(\mathbf{x}|H_1)}{p(\mathbf{x}|H_0)} \stackrel{0}{\leq} 1$$

$$p(\mathbf{x}|H_i) = (2\pi\sigma^2)^{-n/2} \exp\left(-\frac{1}{2\sigma^2} \sum_{j=1}^n (x_j - s_j^{(i)})^2\right)$$

• Similar to the detection of multiple DC levels: minimum Euclidean distance detector $k = \operatorname{argmin}_i D_i^2 = \operatorname{argmin}_i \sum_{j=1}^n (x_j - s_j^{(i)})^2$

• $\mathbf{x} \in \mathbb{R}^2$, 2d case for visualization



... or

$$\begin{split} D_i^2 &= \sum_{j=1}^n (x_j - s_j^{(i)})^2 \\ &= \sum_{j=1}^n x_j^2 - 2 \sum_{j=1}^n x_j s_j^{(i)} + \sum_{j=1}^n (s_j^{(i)})^2 \\ &= \sum_{j=1}^n x_j^2 - 2 \sum_{j=1}^n x_j s_j^{(i)} + \sum_{j=1}^n (s_j^{(i)})^2 \\ T_i(\mathbf{x}) &= \sum_{j=1}^n x_j s_j^{(i)} - \frac{\mathcal{E}^{(i)}}{2} \end{split}$$

• The detector $k = \operatorname{argmax}_i T_i(\mathbf{x})$ is a correlator with a bias term $-\frac{\mathcal{E}^{(i)}}{2}$ to adjust for potentially different signal energies

Probability of error

$$\begin{array}{rcl} P_e & = & P(H_1|H_0)P(H_0) + P(H_0|H_1)P(H_1) \\ & = & \frac{1}{2} \left[\Pr\{T_1(\mathbf{x}) > T_0(\mathbf{x}) | H_0 \} + \Pr\{T_0(\mathbf{x}) > T_1(\mathbf{x}) | H_1 \} \right] \\ P_e & = & \frac{1}{2} \left[\Pr\{T_1(\mathbf{x}) - T_0(\mathbf{x}) > 0 | H_0 \} + \Pr\{T_1(\mathbf{x}) - T_0(\mathbf{x}) < 0 | H_1 \} \right] \\ T(\mathbf{x}) & = & T_1(\mathbf{x}) - T_0(\mathbf{x}), \text{ threshold is } 0 \\ T(\mathbf{x}) & = & \sum_{i=1}^n x_j (s_j^{(1)} - s_j^{(0)}) - \frac{1}{2} \mathcal{E}^{(1)} + \frac{1}{2} \mathcal{E}^{(0)} \end{array}$$

Is $T(\mathbf{x})$ Gaussian?

$$T(\mathbf{x}) = \sum_{j=1}^{n} x_j (s_j^{(1)} - s_j^{(0)}) - \frac{1}{2} \mathcal{E}^{(1)} + \frac{1}{2} \mathcal{E}^{(0)}$$

 $T(\mathbf{x})$ is Gaussian under H_0 and H_1 because x_i 's are iid Gaussian

$$E[T(\mathbf{x})|H_0] = \sum_{j=1}^n s_j^{(0)} (s_j^{(1)} - s_j^{(0)}) - \frac{1}{2} \mathcal{E}^{(1)} + \frac{1}{2} \mathcal{E}^{(0)}$$

$$= \sum_{j=1}^n s_j^{(0)} s_j^{(1)} - \frac{1}{2} \mathcal{E}^{(1)} - \frac{1}{2} \mathcal{E}^{(0)}$$

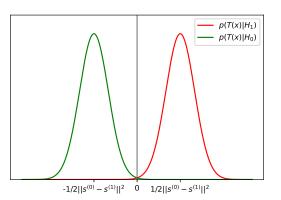
$$= \sum_{j=1}^n (s_j^{(0)} s_j^{(1)} - \frac{1}{2} s_j^{(1)} s_j^{(1)} - \frac{1}{2} s_j^{(0)} s_j^{(0)})$$

$$= \frac{-1}{2} \sum_{j=1}^n (s_j^{(0)} - s_j^{(1)})^2 = \frac{-1}{2} ||\mathbf{s}^{(0)} - \mathbf{s}^{(1)}||^2$$

$$\begin{split} T(\mathbf{x}) &= \sum_{j=1}^n x_j (s_j^{(1)} - s_j^{(0)}) - \frac{1}{2} \mathcal{E}^{(1)} + \frac{1}{2} \mathcal{E}^{(0)} \\ \text{Similarly, } E[T(\mathbf{x})|H_1] &= \frac{1}{2} ||\mathbf{s}^{(0)} - \mathbf{s}^{(1)}||^2 = -E[T(\mathbf{x})|H_0] \\ Var[T(\mathbf{x})|H_0] &= Var \left[\sum_{j=1}^n x_j (s_j^{(1)} - s_j^{(0)}) \right] \\ &= \sum_{j=1}^n Var[x_j] (s_j^{(1)} - s_j^{(0)})^2 \\ &= \sigma^2 ||\mathbf{s}^{(0)} - \mathbf{s}^{(1)}||^2 \end{split}$$

Similarly, $Var[T(\mathbf{x})|H_1] = \sigma^2 ||\mathbf{s}^{(0)} - \mathbf{s}^{(1)}||^2 = Var[T(\mathbf{x})|H_0]$

$$T(\mathbf{x}) = \sum_{j=1}^{n} x_j (s_j^{(1)} - s_j^{(0)}) - \frac{1}{2} \mathcal{E}^{(1)} + \frac{1}{2} \mathcal{E}^{(0)}$$



• Mean shifted Gauss-Gauss problem:

$$\begin{split} P_e &= \frac{1}{2} (\Pr\{T(\mathbf{x}) > 0 | H_0 \} + \Pr\{T(\mathbf{x}) < 0 | H_1 \}) \\ &= \Pr\{T(\mathbf{x}) > 0 | H_0 \} \\ P_e &= Q\left(\frac{\frac{1}{2} ||\mathbf{s}^{(0)} - \mathbf{s}^{(1)}||^2}{\sigma ||\mathbf{s}^{(0)} - \mathbf{s}^{(1)}||}\right) = Q\left(\sqrt{d^2}\right) \\ d^2 &= \frac{||\mathbf{s}^{(0)} - \mathbf{s}^{(1)}||^2}{4\sigma^2} \quad \text{deflection coefficient} \end{split}$$

Binary deterministic signals in WGN: optimal signal design

• **Problem:** How to design $\mathbf{s}^{(0)}, \mathbf{s}^{(1)}$ under energy constraint: $\frac{1}{2}(\mathcal{E}^{(1)} + \mathcal{E}^{(0)}) = \overline{\mathcal{E}} = const.$ to minimize P_e ?

$$\begin{aligned} ||\mathbf{s}^{(0)} - \mathbf{s}^{(1)}||^2 &= (\mathbf{s}^{(0)} - \mathbf{s}^{(1)})^T \cdot (\mathbf{s}^{(0)} - \mathbf{s}^{(1)}) \\ &= \mathbf{s}^{(0)T} \cdot \mathbf{s}^{(0)} + \mathbf{s}^{(1)T} \cdot \mathbf{s}^{(1)} - 2\mathbf{s}^{(1)T} \cdot \mathbf{s}^{(0)} \\ &= 2\overline{\mathcal{E}} - 2\mathbf{s}^{(1)T} \cdot \mathbf{s}^{(0)} \\ &= 2\overline{\mathcal{E}} \left(1 - \underbrace{\frac{\mathbf{s}^{(1)T} \cdot \mathbf{s}^{(0)}}{\frac{1}{2}[||\mathbf{s}^{(0)}||^2 + ||\mathbf{s}^{(1)}||^2]}}_{gs}\right) \end{aligned}$$

• $ho_S = rac{\mathbf{s}^{(1)T}.\mathbf{s}^{(0)}}{1/2[||\mathbf{s}^{(0)}||^2+||\mathbf{s}^{(1)}||^2]} = \text{signal correlation coefficient}$

Binary deterministic signals in WGN: optimal signal design

- $\rho_S = \frac{\mathbf{s}^{(1)T} \cdot \mathbf{s}^{(0)}}{1/2[||\mathbf{s}^{(0)}||^2 + ||\mathbf{s}^{(1)}||^2]} = \text{signal correlation coefficient}$
- $-1 \le \rho_S \le 1$ because

$$\rho_S = \underbrace{\frac{\mathbf{s}^{(1)T} \cdot \mathbf{s}^{(0)}}{||\mathbf{s}^{(0)}|| \times ||\mathbf{s}^{(1)}||}}_{|.| \leq 1 \text{CS Ineq}} \times \underbrace{\frac{||\mathbf{s}^{(0)}|| \times ||\mathbf{s}^{(1)}||}{\frac{1}{2}[||\mathbf{s}^{(0)}||^2 + ||\mathbf{s}^{(1)}||^2]}}_{\leq 1 \text{AG Ineq}}$$

- CS Ineq: Cauchy–Schwarz inequality
- AG Ineq: Inequality of arithmetic and geometric means $\frac{ab}{1/2(a^2+b^2)} \leq 1, \forall a,b,a^2+b^2 \neq 0$

Binary deterministic signals in WGN: optimal signal design

$$P_e = Q\left(\sqrt{\frac{||\mathbf{s}^{(0)} - \mathbf{s}^{(1)}||^2}{4\sigma^2}}\right)$$
$$= Q\left(\sqrt{\frac{2\overline{\mathcal{E}}(1 - \rho_S)}{4\sigma^2}}\right)$$

will be minimum if $\rho_S = -1$, i. e., anticorrelated signals

$$\rho_S = -1 \Leftrightarrow \begin{cases} ||\mathbf{s}^{(0)}|| = ||\mathbf{s}^{(1)}|| & \text{(from AG ineq)} \\ \text{and} \\ \mathbf{s}^{(0)} = -\mathbf{s}^{(1)} & \text{(from CS ineq)} \end{cases}$$

For this optimal design: $P_e = Q\left(\sqrt{\overline{\mathcal{E}}/\sigma^2}\right)$