



# Detection Theory

Chapter 7. Deterministic Signals with Unknown Parameters

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## Background

- Statistical Decision Theory I
  - PDF for assumed hypothesis is **completely** known.
  - Approaches:
    - Neyman-Pearson theorem
    - Bayesian approach based on minimization of Bayes risk
  - Signal model
    - Deterministic signal
    - Random signal



## Outline

- Background
- Importance of signal information
- Unknown amplitude
- Unknown arrival time
- Sinusoidal detection
- Classical linear model



## Background (Cont.)

- Statistical Decision Theory II
  - PDF has **unknown** parameters (in this chapter **deterministic** signals)
  - Approaches:

- UMP does not **usually** exist
- Generalized Likelihood Ratio Test (GLRT)  
Decide  $\mathcal{H}_1$  if

$$L_G(\mathbf{x}) = \frac{p(\mathbf{x}; \hat{\theta}_1, \mathcal{H}_1)}{p(\mathbf{x}; \hat{\theta}_0, \mathcal{H}_0)} > \gamma$$

- Bayesian approach  
Decide  $\mathcal{H}_1$  if

$$\frac{p(\mathbf{x}; \mathcal{H}_1)}{p(\mathbf{x}; \mathcal{H}_0)} = \frac{\int p(\mathbf{x} | \hat{\theta}_1, \mathcal{H}_1) p(\hat{\theta}_1) d\hat{\theta}_1}{\int p(\mathbf{x} | \hat{\theta}_0, \mathcal{H}_0) p(\hat{\theta}_0) d\hat{\theta}_0} > \gamma$$

## Importance of Signal Information



- Assume there is **no knowledge** of signal

$$\mathcal{H}_0 : x[n] = \omega[n] \quad n = 0, 1, \dots, N-1$$

$$\mathcal{H}_1 : x[n] = s[n] + \omega[n] \quad n = 0, 1, \dots, N-1$$

$\omega[n] \sim$  WGN with variance  $\sigma^2$

$s[n] \sim$  deterministic and completely unknown

- A GLRT decides  $\mathcal{H}_1$  if

$$\frac{p(\mathbf{x}; \hat{s}[0], \dots, \hat{s}[N-1], \mathcal{H}_1)}{p(\mathbf{x}; \mathcal{H}_0)} > \gamma$$

where  $\hat{s}[n]$  is MLE of  $s[n]$  for  $n = 0, 1, \dots, N-1$

## Importance of Signal Information (Cont.)



- Under  $\mathcal{H}_0$  the PDF of  $x$

$$p(\mathbf{x}; \mathcal{H}_0) = \frac{1}{(2\pi\sigma^2)^{\frac{N}{2}}} \exp\left(-\frac{1}{2\sigma^2} \sum_{n=0}^{N-1} x[n]^2\right)$$

- Under  $\mathcal{H}_1$  the PDF of  $x$

$$p(\mathbf{x}; \hat{s}[0], \dots, \hat{s}[N-1], \mathcal{H}_1) = \frac{1}{(2\pi\sigma^2)^{\frac{N}{2}}} \exp\left[-\frac{1}{2\sigma^2} \sum_{n=0}^{N-1} (x[n] - \hat{s}[n])^2\right]$$

$$\hat{s}[n] = x[n]$$

- Thus,

$$\frac{\frac{1}{(2\pi\sigma^2)^{\frac{N}{2}}}}{\frac{1}{(2\pi\sigma^2)^{\frac{N}{2}}} \exp\left(-\frac{1}{2\sigma^2} \sum_{n=0}^{N-1} x[n]^2\right)} > \gamma \Rightarrow T(X) = \sum_{n=0}^{N-1} x[n]^2 = \sum_{n=0}^{N-1} x[n] \hat{s}[n] > \gamma'$$

energy detector

## Importance of Signal Information (Cont.)



- Detection performance

$$P_D = Q\left(Q^{-1}(P_{FA}) - \sqrt{d^2}\right)$$

$$d_{ED}^2 = \frac{\left(\frac{\varepsilon}{\sigma^2}\right)^2}{2N} \quad d_{MF}^2 = \frac{\varepsilon}{\sigma^2}$$

- Loss in performance

$$10 \log_{10} \frac{d_{MF}^2}{d_{ED}^2} = 10 \log_{10} \frac{2N}{\frac{\varepsilon}{\sigma^2}} \text{ dB}$$

Matched filter **coherently** combines data

Energy detector **incoherently** combines data

## Unknown Amplitude



- Detecting a **deterministic** signal with **unknown amplitude** in WGN

$$\mathcal{H}_0 : x[n] = \omega[n] \quad n = 0, 1, \dots, N-1$$

$$\mathcal{H}_1 : x[n] = A s[n] + \omega[n] \quad n = 0, 1, \dots, N-1$$

$A$ : unknown amplitude

$\omega[n] \sim$  WGN with variance  $\sigma^2$

$s[n]$ : deterministic and completely known

- UMP test
- GLRT
- Bayesian approach

## Unknown Amplitude (Cont.)



- **UMP test:** LRT decides  $\mathcal{H}_1$  if

$$\frac{p(\mathbf{x}; \mathcal{H}_1)}{p(\mathbf{x}; \mathcal{H}_0)} > \gamma \Rightarrow \frac{\frac{1}{(2\pi\sigma^2)^{\frac{N}{2}}} \exp\left[-\frac{1}{2\sigma^2} \sum_{n=0}^{N-1} (x[n] - As[n])^2\right]}{\frac{1}{(2\pi\sigma^2)^{\frac{N}{2}}} \exp\left(-\frac{1}{2\sigma^2} \sum_{n=0}^{N-1} x[n]^2\right)} > \gamma$$

$$A \sum_{n=0}^{N-1} x[n]s[n] > \gamma' \Rightarrow \begin{cases} \sum_{n=0}^{N-1} x[n]s[n] > \frac{\gamma'}{A} & A > 0 \\ \sum_{n=0}^{N-1} x[n]s[n] < \frac{\gamma'}{A} & A < 0 \end{cases}$$

UMP does not exist

## Unknown Amplitude (Cont.)



- **GLRT** decides  $\mathcal{H}_1$  if

$$\frac{p(X; \hat{A}, \mathcal{H}_1)}{p(X; \mathcal{H}_0)} > \gamma \Rightarrow \frac{\frac{1}{(2\pi\sigma^2)^{\frac{N}{2}}} \exp\left[-\frac{1}{2\sigma^2} \sum_{n=0}^{N-1} (x[n] - \hat{A}s[n])^2\right]}{\frac{1}{(2\pi\sigma^2)^{\frac{N}{2}}} \exp\left(-\frac{1}{2\sigma^2} \sum_{n=0}^{N-1} x[n]^2\right)} > \gamma$$

$\hat{A}$  is MLE of  $A$  under  $\mathcal{H}_1$

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

$$T(X) = \left(\sum_{n=0}^{N-1} x[n]s[n]\right)^2 > \gamma' \quad \text{or} \quad \left|\sum_{n=0}^{N-1} x[n]s[n]\right| > \sqrt{\gamma'}$$

## Unknown Amplitude (Cont.)



- **GLRT detector performance**

$$P_{FA} = \Pr\left\{|u(x)| > \sqrt{\gamma'}; \mathcal{H}_0\right\}$$

$$P_D = \Pr\left\{|u(x)| > \sqrt{\gamma'}; \mathcal{H}_1\right\}$$

$$\left|\sum_{n=0}^{N-1} x[n]s[n]\right| > \sqrt{\gamma'}$$

$$u(x) = \sum_{n=0}^{N-1} x[n]s[n] \sim \begin{cases} N\left(0, \sigma^2 \sum_{n=0}^{N-1} s^2[n]\right) & \text{under } \mathcal{H}_0 \\ N\left(A \sum_{n=0}^{N-1} s^2[n], \sigma^2 \sum_{n=0}^{N-1} s^2[n]\right) & \text{under } \mathcal{H}_1 \end{cases}$$

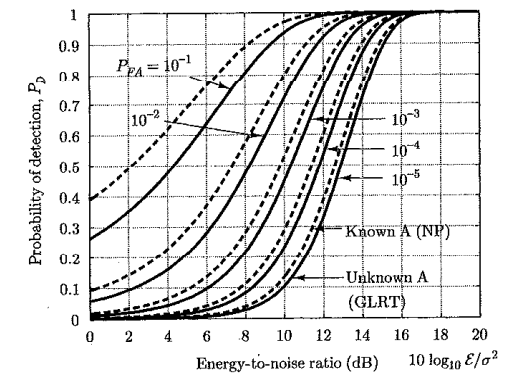
## Unknown Amplitude (Cont.)



- **GLRT detector performance**

$$P_D = Q\left(Q^{-1}(P_{FA}/2) - \sqrt{d^2}\right) + Q\left(Q^{-1}(P_{FA}/2) + \sqrt{d^2}\right)$$

$$\text{where } d^2 = \frac{\varepsilon}{\sigma^2}$$



## Unknown Amplitude (Cont.)



- Bayesian approach, under  $\mathcal{H}_1$

$$\mathbf{x} = \mathbf{S}A + \mathbf{w}$$

$$\mathbf{x} = \mathbf{H}\theta + \mathbf{w}$$

A random variable with PDF  $N(\mu_A, \sigma_A^2)$

$$\mathbf{s} = [s[0], s[1], \dots, s[N-1]]^T$$

$\mathbf{w}$  WGN with variance  $(0, \sigma^2 \mathbf{I})$

- NP test decides  $\mathcal{H}_1$  if (results in Section 5.6)

$$T'(\mathbf{x}) = \mathbf{x}^T (\mathbf{H}\mathbf{C}_\theta \mathbf{H}^T + \mathbf{C}_\omega)^{-1} \mathbf{H}\mu_\theta$$

$$+ \frac{1}{2} \mathbf{x}^T \mathbf{C}_\omega^{-1} \mathbf{H}\mathbf{C}_\theta \mathbf{H}^T (\mathbf{H}\mathbf{C}_\theta \mathbf{H}^T + \mathbf{C}_\omega)^{-1} \mathbf{x} > \gamma'$$

$$\begin{aligned} \mu_\theta &= \mu_A \\ \mathbf{C}_\theta &= \sigma_A^2 \\ \mathbf{C}_\omega &= \sigma^2 \mathbf{I} \end{aligned}$$

## Unknown Amplitude (Cont.)



- NP test statistic

$$T'(\mathbf{x}) = \frac{\mu_A}{\sigma^2 + \sigma_A^2} \frac{\mathbf{x}^T \mathbf{s} + \frac{\sigma_A^2}{\sigma^2 + \sigma_A^2} (\mathbf{x}^T \mathbf{s})^2}{2\sigma^2 (\sigma^2 + \sigma_A^2 \mathbf{s}^T \mathbf{s})}$$

Diagram labels: **correlator** (orange cloud) points to  $\mathbf{x}^T \mathbf{s}$ ; **Squared-correlator** (green cloud) points to  $(\mathbf{x}^T \mathbf{s})^2$ .

- if  $\sigma_A^2 = 0 \Rightarrow T'(\mathbf{x}) = \frac{1}{\sigma^2} \mathbf{x}^T \mu_A \mathbf{s}$  (known amplitude case)
- if  $\sigma_A^2 \rightarrow \infty \Rightarrow T'(\mathbf{x}) = \frac{1}{2\sigma^2 \mathbf{s}^T \mathbf{s}} (\mathbf{x}^T \mathbf{s})^2$  (unknown amplitude)
- Using Bayesian detector we require knowledge of  $\mu_A$  and  $\sigma_A^2$ .

## Unknown Arrival Time



- Detecting a **deterministic** signal with **unknown arrival time** in WGN

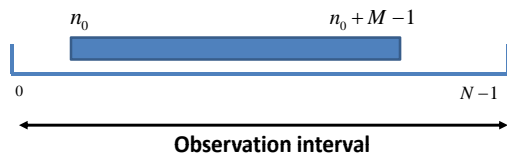
$$\mathcal{H}_0 : x[n] = \omega[n] \quad n = 0, 1, \dots, N-1$$

$$\mathcal{H}_1 : x[n] = s[n - n_0] + \omega[n] \quad n = 0, 1, \dots, N-1$$

$n_0$  unknown delay

$\omega[n]$  WGN with variance  $\sigma^2$

$s[n]$  deterministic and known  $[0, M-1]$



## Unknown Arrival Time (Cont.)



- GLRT decides  $\mathcal{H}_1$  if

$$\frac{p(\mathbf{x}; \hat{n}_0, \mathcal{H}_1)}{p(\mathbf{x}; \mathcal{H}_0)} > \gamma$$

$\hat{n}_0$  is MLE of  $n_0$  under  $\mathcal{H}_1$

$$\max \left( \sum_{n=n_0}^{n_0+M-1} x[n] s[n - n_0] \right)$$

- Under  $\mathcal{H}_1$

$$p(\mathbf{x}; n_0, \mathcal{H}_1) = \prod_{n=0}^{n_0-1} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{1}{2\sigma^2} x^2[n]\right) \prod_{n=n_0}^{n_0+M-1} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left[-\frac{1}{2\sigma^2} (x[n] - s[n - n_0])^2\right] \prod_{n=n_0+M}^{N-1} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{1}{2\sigma^2} x^2[n]\right)$$

The diagram shows the signal duration from  $n_0$  to  $n_0 + M - 1$  and the observation interval from  $0$  to  $N-1$ .

## Unknown Arrival Time (Cont.)

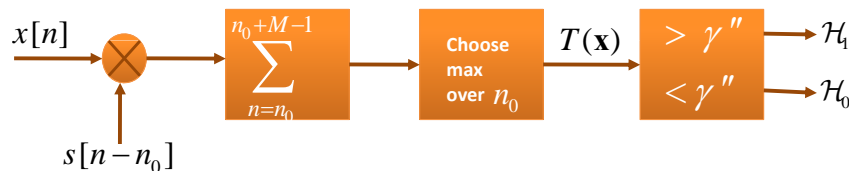


- Test statistic

$$-\frac{1}{2\sigma^2} \sum_{n=\hat{n}_0}^{\hat{n}_0+M-1} (-2x[n]s[n-\hat{n}_0] - \underbrace{s^2[n-\hat{n}_0]}_{\sum_{n=\hat{n}_0}^{\hat{n}_0+M-1} s^2[n-\hat{n}_0] = \varepsilon}) > \gamma'$$

$$T(\mathbf{x}) = \sum_{n=\hat{n}_0}^{\hat{n}_0+M-1} x[n]s[n-\hat{n}_0] > \gamma''$$

$$T(\mathbf{x}) = \max_{n_0 \in [0, N-M]} \sum_{n=n_0}^{n_0+M-1} x[n]s[n-n_0] > \gamma''$$



## Unknown Arrival Time (Cont.)



- Detection performance of **GLRT** is **difficult!**

PDF of **correlated** Gaussian random variable has to be determined.

$$P_{FA} = \Pr \left\{ \max_{n_0 \in [0, N-M]} \sum_{n=n_0}^{n_0+M-1} x[n]s[n-n_0] > \gamma'; \mathcal{H}_0 \right\}$$

$$P_D = \Pr \left\{ \max_{n_0 \in [0, N-M]} \sum_{n=n_0}^{n_0+M-1} x[n]s[n-n_0] > \gamma'; \mathcal{H}_1 \right\}$$

- Delay is less than sampling interval

$$T(\mathbf{x}) = \max_{n_0 \in [0, N-M]} \int_{-\frac{1}{2}}^{\frac{1}{2}} X(f) |S(f) \exp(-j2\pi f n_0)|^* df$$

## Sinusoidal Detection



- Detection of a sinusoid in WGN

$$\mathcal{H}_0 : x[n] = \omega[n] \quad n = 0, 1, \dots, N-1$$

$$\mathcal{H}_1 : x[n] = \begin{cases} \omega[n] & n = 0, 1, \dots, n_0 - 1, n_0 + M, \dots, N-1 \\ A \cos(2\pi f_0 n + \varphi) + \omega[n] & n = n_0, n_0 + 1, \dots, n_0 + M - 1 \end{cases}$$

- GLRT approach

- $A$  unknown
- $A, \varphi$  unknown
- $A, \varphi, f_0$  unknown
- $A, \varphi, f_0, n_0$  unknown

## Sinusoidal Detection (Cont.)



- Detection of a sinusoid in WGN with **unknown amplitude** and **phase**, **GLRT** decides  $\mathcal{H}_1$  if

$$\frac{p(\mathbf{x}; \hat{A}, \hat{\varphi}, \mathcal{H}_1)}{p(\mathbf{x}; \mathcal{H}_0)} > \gamma$$

$\hat{A}$  and  $\hat{\varphi}$  are MLE of  $A$  and  $\varphi$

$$\hat{A} = \sqrt{\hat{\alpha}_1^2 + \hat{\alpha}_2^2}$$

$$\hat{\alpha}_1 = \frac{2}{N} \sum_{n=0}^{N-1} x[n] \cos 2\pi f_0 n$$

$$\hat{\varphi} = \arctan \left( \frac{-\hat{\alpha}_2}{\hat{\alpha}_1} \right)$$

$$\hat{\alpha}_2 = \frac{2}{N} \sum_{n=0}^{N-1} x[n] \sin 2\pi f_0 n$$

## Sinusoidal Detection (Cont.)



- We decide  $\mathcal{H}_1$  if

$$\frac{\frac{1}{(2\pi\sigma^2)^{\frac{N}{2}}} \exp\left[-\frac{1}{2\sigma^2} \sum_{n=0}^{N-1} (x[n] - \hat{A} \cos(2\pi f_0 n + \hat{\phi}))^2\right]}{\frac{1}{(2\pi\sigma^2)^{\frac{N}{2}}} \exp\left[-\frac{1}{2\sigma^2} \sum_{n=0}^{N-1} x^2[n]\right]} > \gamma$$

$$\left| \sum_{n=0}^{N-1} x[n] \exp(-j2\pi f_0 n) \right|^2 = I(f_0) > \gamma'$$

periodogram detector

incoherent or quadrature MF

## Sinusoidal Detection (Cont.)



- GLRT detection performance

$$P_{FA} = \Pr\{I(f_0) > \gamma'; \mathcal{H}_0\}$$

$$P_D = \Pr\{I(f_0) > \gamma'; \mathcal{H}_1\}$$

$$I(f_0) = \xi_1^2 + \xi_2^2 \quad \text{jointly Gaussian} \quad \xi = [\xi_1 \ \xi_2]^T$$

$$\xi_1 = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} x[n] \cos 2\pi f_0 n \quad \rightarrow \quad \begin{cases} N \left( 0, \frac{\sigma^2}{2} I \right) & \text{under } \mathcal{H}_0 \\ N \left( \begin{bmatrix} \frac{\sqrt{N}}{2} A \cos \varphi \\ -\frac{\sqrt{N}}{2} A \sin \varphi \end{bmatrix}, \frac{\sigma^2}{2} I \right) & \text{under } \mathcal{H}_1 \end{cases}$$

## Sinusoidal Detection (Cont.)



- GLRT detection performance

$$P_{FA} = Q_{\chi^2_2} \left( \frac{2\gamma'}{\sigma^2} \right) = \exp\left(-\frac{\gamma'}{\sigma^2}\right)$$

$$P_D = Q_{\chi^2_2(\lambda)} \left( \frac{2\gamma'}{\sigma^2} \right)$$

$$P_D = Q_{\chi^2_2(\lambda)} \left( 2 \ln \frac{1}{P_{FA}} \right)$$

$$\lambda = \frac{NA^2}{2\sigma^2}$$

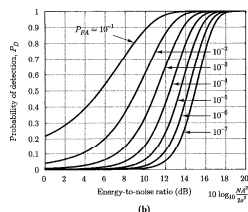
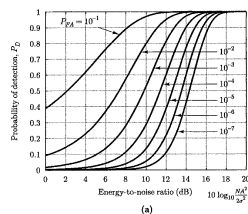


Figure 7.6. GLRT detection performance for sinusoid in WGN (a) Unknown amplitude (b) Unknown amplitude, phase.

## Sinusoidal Detection (Cont.)



- Detection of a sinusoid in WGN with **unknown**  $A, \varphi, f_0, n_0$   
GLRT decides  $\mathcal{H}_1$  if

$$\frac{p(\mathbf{x}; \hat{A}, \hat{\phi}, \hat{f}_0, \hat{n}_0, \mathcal{H}_1)}{p(\mathbf{x}; \mathcal{H}_0)} > \gamma$$

$\hat{A}, \hat{\phi}, \hat{f}_0$  and  $\hat{n}_0$  are MLE of  $A, \varphi, f_0$  and  $n_0$

$$\hat{A} = \sqrt{\hat{\alpha}_1^2 + \hat{\alpha}_2^2}$$

$$\hat{\phi} = \arctan \left( \frac{-\hat{\alpha}_2}{\hat{\alpha}_1} \right)$$

$$\hat{\alpha}_1 = \frac{2}{M} \sum_{n=n_0}^{n_0+M-1} x[n] \cos 2\pi \hat{f}_0 (n - n_0)$$

$$\hat{\alpha}_2 = \frac{2}{M} \sum_{n=n_0}^{n_0+M-1} x[n] \sin 2\pi \hat{f}_0 (n - n_0)$$

## Sinusoidal Detection (Cont.)



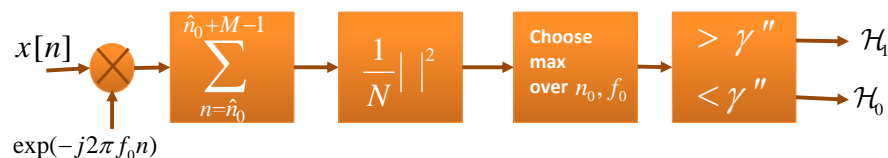
- After simplification,

$$\ln \frac{p(\mathbf{x}; \hat{A}, \hat{\phi}, \hat{f}_0, n_0, \mathcal{H}_1)}{p(\mathbf{x}; \mathcal{H}_0)} = \frac{I_{n_0}(\hat{f}_0)}{\sigma^2}$$

$$\text{where } I_{n_0}(\hat{f}_0) = \frac{1}{M} \left| \sum_{n=n_0}^{n_0+M-1} x[n] \exp(-j2\pi \hat{f}_0 n) \right|^2$$

- We decide  $\mathcal{H}_1$  if

$$\max_{n_0, f_0} \frac{I_{n_0}(f_0)}{\sigma^2} > \gamma'$$



## Classical Linear Model



- Linear Bayesian model
  - Detection problem with **unknown** signal parameters converts to **general Gaussian problem**
  - NP** detector
- Classical linear model
  - Parameters assumed **deterministic**
  - GLRT

## GLRT Classical Linear Model



- Assume that

$$\mathbf{x} = \mathbf{H}\boldsymbol{\theta} + \mathbf{w}$$

$\mathbf{H}$  is known  $N \times p$  observation matrix of rank  $p$

$\boldsymbol{\theta}$  is  $p \times 1$  vector of parameters

$\mathbf{w}$  is  $N \times 1$  noise vector with PDF  $N(0, \sigma^2 I)$

- GLRT for hypothesis testing problem

$$\mathcal{H}_0 : A\boldsymbol{\theta} = \mathbf{b}$$

$$\mathcal{H}_1 : A\boldsymbol{\theta} \neq \mathbf{b}$$

$\mathbf{A}$  is  $r \times p$  matrix of rank  $r$

$\mathbf{b}$  is  $r \times 1$  vector

$A\boldsymbol{\theta} = \mathbf{b}$  is consistent set of linear equations

## GLRT Classical Linear Model (Cont.)



- We decide  $\mathcal{H}_1$  if

$$T(\mathbf{x}) = 2 \ln L_G(\mathbf{x}) = \frac{(\mathbf{A}\hat{\boldsymbol{\theta}}_1 - \mathbf{b})^T [\mathbf{A}(\mathbf{H}^T \mathbf{H})^{-1} \mathbf{A}^T]^{-1} (\mathbf{A}\hat{\boldsymbol{\theta}}_1 - \mathbf{b})}{\sigma^2} > \gamma'$$

$$\hat{\boldsymbol{\theta}}_1 = (\mathbf{H}^T \mathbf{H})^{-1} \mathbf{H}^T \mathbf{x}$$

$\hat{\boldsymbol{\theta}}_1$  is the MLE of  $\boldsymbol{\theta}$  under  $\mathcal{H}_1$

## GLRT Classical Linear Model (Cont.)



- Detection performance

$$P_{FA} = Q_{\chi_r^2}(\gamma')$$

$$P_D = Q_{\chi_r^2(\lambda)}(\gamma')$$

$$\lambda = \frac{(\mathbf{A}\hat{\boldsymbol{\theta}}_1 - \mathbf{b})^T [\mathbf{A}(\mathbf{H}^T \mathbf{H})^{-1} \mathbf{A}^T]^{-1} (\mathbf{A}\hat{\boldsymbol{\theta}}_1 - \mathbf{b})}{\sigma^2}$$

## GLRT Classical Linear Model (Cont.)



- Unknown amplitude signal in WGN

$$\mathcal{H}_0: x[n] = \omega[n] \quad n = 0, 1, \dots, N-1$$

$$\mathcal{H}_1: x[n] = A s[n] + \omega[n] \quad n = 0, 1, \dots, N-1$$



$$\mathcal{H}_0: x[n] = A s[n] + \omega[n], A = 0 \quad n = 0, 1, \dots, N-1$$

$$\mathcal{H}_1: x[n] = A s[n] + \omega[n], A \neq 0 \quad n = 0, 1, \dots, N-1$$

$$\mathbf{x} = \mathbf{H}\boldsymbol{\theta} + \mathbf{w}$$

$$\mathbf{H} = [s[0], s[1], \dots, s[N-1]]^T$$

$$\boldsymbol{\theta} = A$$



$$\mathcal{H}_0: \theta = 0$$

$$\mathcal{H}_1: \theta \neq 0$$

## GLRT Classical Linear Model (Cont.)



- We decide  $\mathcal{H}_1$  if

$$T(\mathbf{x}) = 2 \ln L_G(\mathbf{x}) = \frac{(\mathbf{A}\hat{\boldsymbol{\theta}}_1 - \mathbf{b})^T [\mathbf{A}(\mathbf{H}^T \mathbf{H})^{-1} \mathbf{A}^T]^{-1} (\mathbf{A}\hat{\boldsymbol{\theta}}_1 - \mathbf{b})}{\sigma^2} > \gamma'$$

$$A = 1, b = 0$$



$$T(\mathbf{x}) = \frac{\hat{\boldsymbol{\theta}}_1^T \mathbf{H}^T \mathbf{H} \hat{\boldsymbol{\theta}}_1}{\sigma^2} = \frac{\mathbf{H}^T \mathbf{H} \hat{\boldsymbol{\theta}}_1^2}{\sigma^2}$$

$$\hat{\boldsymbol{\theta}}_1 = (\mathbf{H}^T \mathbf{H})^{-1} \mathbf{H}^T \mathbf{x}$$

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



$$T(\mathbf{x}) = \frac{\left( \sum_{n=0}^{N-1} x[n] s[n] \right)^2}{\sigma^2 \sum_{n=0}^{N-1} s^2[n]} > \gamma'$$

## GLRT Classical Linear Model (Cont.)



- Detection performance

$$P_{FA} = Q_{\chi_r^2}(\gamma')$$

$$P_D = Q_{\chi_r^2(\lambda)}(\gamma')$$

$$\text{where } \lambda = \frac{\mathbf{H}^T \mathbf{H} \theta_1^2}{\sigma^2} = \frac{A^2 \sum_{n=0}^{N-1} s^2[n]}{\sigma^2} = \frac{\varepsilon}{\sigma^2}$$



$$P_D = Q\left(Q^{-1}(P_{FA}/2) - \sqrt{d^2}\right) + Q\left(Q^{-1}(P_{FA}/2) + \sqrt{d^2}\right)$$

$$\text{where } d^2 = \frac{\varepsilon}{\sigma^2}$$