

# 统计信号处理

## 第十四章

# 复合假设检验 II (基本方法II)

清华大学电子工程系  
李洪 副教授

2023. 5

# 内容概要

- 一、大数据量时GLRT等效方法
- 二、大数据量时GLRT的性能
- 三、局部最大势检测
- 四、最小错误概率检测——广义ML检测
- 五、应用案例
- 六、小结

# 一、大数据量时GLRT等效方法

假设检验模型

$$H_0 : \boldsymbol{\theta} = \boldsymbol{\theta}_0$$

$$H_1 : \boldsymbol{\theta} \neq \boldsymbol{\theta}_0 \quad (\boldsymbol{\theta}_1 \approx \boldsymbol{\theta}_0) \quad \text{弱信号}$$

采用NP准则，若广义似然比

$$L_G(\mathbf{x}) = \frac{p(\mathbf{x}; \hat{\boldsymbol{\theta}}_1)}{p(\mathbf{x}; \boldsymbol{\theta}_0)} > \gamma, \quad \text{则判 } H_1$$

隐含前提：不同假设下，观察数据具有相同的pdf形式

$N \rightarrow \infty$  时，MLE是渐近有效的，

$$\frac{\partial \ln p(\mathbf{x}; \boldsymbol{\theta})}{\partial \boldsymbol{\theta}} = \mathbf{I}(\boldsymbol{\theta})(\hat{\boldsymbol{\theta}}_1 - \boldsymbol{\theta}) \approx \mathbf{I}(\hat{\boldsymbol{\theta}}_1)(\hat{\boldsymbol{\theta}}_1 - \boldsymbol{\theta}) \rightarrow$$

$$\ln p(\mathbf{x}; \boldsymbol{\theta}) = -\frac{1}{2}(\hat{\boldsymbol{\theta}}_1 - \boldsymbol{\theta})^T \mathbf{I}(\hat{\boldsymbol{\theta}}_1)(\hat{\boldsymbol{\theta}}_1 - \boldsymbol{\theta}) + \ln p(\mathbf{x}; \hat{\boldsymbol{\theta}}_1)$$

$$\ln p(\mathbf{x}; \boldsymbol{\theta}) = -\frac{1}{2}(\hat{\boldsymbol{\theta}}_1 - \boldsymbol{\theta})^T \mathbf{I}(\hat{\boldsymbol{\theta}}_1)(\hat{\boldsymbol{\theta}}_1 - \boldsymbol{\theta}) + \ln p(\mathbf{x}; \hat{\boldsymbol{\theta}}_1) \quad \rightarrow$$

$$p(\mathbf{x}; \boldsymbol{\theta}) = p(\mathbf{x}; \hat{\boldsymbol{\theta}}_1) \exp \left\{ -\frac{1}{2}(\hat{\boldsymbol{\theta}}_1 - \boldsymbol{\theta})^T \mathbf{I}(\hat{\boldsymbol{\theta}}_1)(\hat{\boldsymbol{\theta}}_1 - \boldsymbol{\theta}) \right\}$$

$$L_G(\mathbf{x}) = \frac{p(\mathbf{x}; \hat{\boldsymbol{\theta}}_1)}{p(\mathbf{x}; \boldsymbol{\theta}_0)}$$

$$\rightarrow L_G(\mathbf{x}) = \frac{p(\mathbf{x}; \hat{\boldsymbol{\theta}}_1)}{p(\mathbf{x}; \hat{\boldsymbol{\theta}}_1) \exp \left\{ -\frac{1}{2}(\hat{\boldsymbol{\theta}}_1 - \boldsymbol{\theta}_0)^T \mathbf{I}(\hat{\boldsymbol{\theta}}_1)(\hat{\boldsymbol{\theta}}_1 - \boldsymbol{\theta}_0) \right\}}$$

$$\rightarrow 2 \ln L_G(\mathbf{x}) = (\hat{\boldsymbol{\theta}}_1 - \boldsymbol{\theta}_0)^T \mathbf{I}(\hat{\boldsymbol{\theta}}_1)(\hat{\boldsymbol{\theta}}_1 - \boldsymbol{\theta}_0)$$

$$T_W(\mathbf{x}) = (\hat{\boldsymbol{\theta}}_1 - \boldsymbol{\theta}_0)^T \mathbf{I}(\hat{\boldsymbol{\theta}}_1)(\hat{\boldsymbol{\theta}}_1 - \boldsymbol{\theta}_0)$$

前提条件：

- 双边检测
- 弱信号
- 大数据量
- 相同PDF形式

- 无需比较PDF
- 但仍需求MLE

Wald检验

$N \rightarrow \infty$  时

$$\frac{\partial \ln p(\mathbf{x}; \boldsymbol{\theta})}{\partial \boldsymbol{\theta}} = \mathbf{I}(\boldsymbol{\theta})(\hat{\boldsymbol{\theta}}_1 - \boldsymbol{\theta}) \quad \longrightarrow \quad \hat{\boldsymbol{\theta}}_1 - \boldsymbol{\theta} = \mathbf{I}^{-1}(\boldsymbol{\theta}) \frac{\partial \ln p(\mathbf{x}; \boldsymbol{\theta})}{\partial \boldsymbol{\theta}}$$

$$\longrightarrow \quad \hat{\boldsymbol{\theta}}_1 - \boldsymbol{\theta}_0 = \mathbf{I}^{-1}(\boldsymbol{\theta}_0) \left. \frac{\partial \ln p(\mathbf{x}; \boldsymbol{\theta})}{\partial \boldsymbol{\theta}} \right|_{\boldsymbol{\theta}=\boldsymbol{\theta}_0}$$

**Wald检验:**  $2 \ln L_G(\mathbf{x}) = (\hat{\boldsymbol{\theta}}_1 - \boldsymbol{\theta}_0)^T \mathbf{I}(\hat{\boldsymbol{\theta}}_1)(\hat{\boldsymbol{\theta}}_1 - \boldsymbol{\theta}_0)$

$$2 \ln L_G(\mathbf{x}) = \left( \left. \frac{\partial \ln p(\mathbf{x}; \boldsymbol{\theta})}{\partial \boldsymbol{\theta}} \right|_{\boldsymbol{\theta}=\boldsymbol{\theta}_0} \right)^T \underbrace{\mathbf{I}^{-1}(\boldsymbol{\theta}_0) \mathbf{I}(\hat{\boldsymbol{\theta}}_1) \mathbf{I}^{-1}(\boldsymbol{\theta}_0)} \left. \frac{\partial \ln p(\mathbf{x}; \boldsymbol{\theta})}{\partial \boldsymbol{\theta}} \right|_{\boldsymbol{\theta}=\boldsymbol{\theta}_0}$$

$$\longrightarrow 2 \ln L_G(\mathbf{x}) = \left( \left. \frac{\partial \ln p(\mathbf{x}; \boldsymbol{\theta})}{\partial \boldsymbol{\theta}} \right|_{\boldsymbol{\theta}=\boldsymbol{\theta}_0} \right)^T \mathbf{I}^{-1}(\boldsymbol{\theta}_0) \left. \frac{\partial \ln p(\mathbf{x}; \boldsymbol{\theta})}{\partial \boldsymbol{\theta}} \right|_{\boldsymbol{\theta}=\boldsymbol{\theta}_0}$$

$$T_R(\mathbf{x}) = \left( \left. \frac{\partial \ln p(\mathbf{x}; \boldsymbol{\theta})}{\partial \boldsymbol{\theta}} \right|_{\boldsymbol{\theta}=\boldsymbol{\theta}_0} \right)^T \mathbf{I}^{-1}(\boldsymbol{\theta}_0) \left. \frac{\partial \ln p(\mathbf{x}; \boldsymbol{\theta})}{\partial \boldsymbol{\theta}} \right|_{\boldsymbol{\theta}=\boldsymbol{\theta}_0}$$

前提条件:

- 双边检测
- 弱信号
- 大数据量
- 相同PDF形式

- 无需比较PDF
- 无需求MLE

Rao检验

## 例：WGN中未知信号检测——Wald与Rao检验

$$H_0 : x[n] = w[n]$$

$$H_1 : x[n] = A + w[n]$$

其中信号电平  $A$  ( $-\infty < A < +\infty$ ) 是未知的。噪声  $w[n]$  是方差为  $\sigma^2$  的WGN。如何检测是否存在信号？

Wald检验：  $T_w(\mathbf{x}) = (\hat{\theta}_1 - \theta_0)^T \mathbf{I}(\hat{\theta}_1)(\hat{\theta}_1 - \theta_0)$

$$p(\mathbf{x}; A, H_1) = \frac{1}{(2\pi\sigma^2)^{\frac{N}{2}}} \exp \left\{ -\frac{1}{2\sigma^2} \sum_{n=0}^{N-1} (x[n] - A)^2 \right\}$$

$$\frac{\partial \ln p(\mathbf{x}; A, H_1)}{\partial A} = \frac{1}{\sigma^2} \sum_{n=0}^{N-1} (x[n] - A) \quad \Rightarrow \quad \hat{\theta}_1 = \hat{A} = \bar{x}$$

$$\frac{\partial^2 \ln p(\mathbf{x}; A, H_1)}{\partial A^2} = -\frac{N}{\sigma^2} \quad \Rightarrow \quad \mathbf{I}(\hat{\theta}_1) = \mathbf{I}(\hat{A}) = \frac{N}{\sigma^2}$$

$$\theta_0 = 0$$

$$T_w(\mathbf{x}) = \frac{N\bar{x}^2}{\sigma^2} \quad \Rightarrow \quad T'_w(\mathbf{x}) = \bar{x}^2$$

## 例：WGN中未知信号检测——Wald与Rao检验

$$H_0 : x[n] = w[n]$$

$$H_1 : x[n] = A + w[n]$$

其中信号电平  $A$  ( $-\infty < A < +\infty$ ) 是未知的。噪声  $w[n]$  是方差为  $\sigma^2$  的WGN。如何检测是否存在信号？

$$\text{Rao检验: } T_R(\mathbf{x}) = \left( \left. \frac{\partial \ln p(\mathbf{x}; \boldsymbol{\theta})}{\partial \boldsymbol{\theta}} \right|_{\boldsymbol{\theta}=\boldsymbol{\theta}_0} \right)^T \mathbf{I}^{-1}(\boldsymbol{\theta}_0) \left. \frac{\partial \ln p(\mathbf{x}; \boldsymbol{\theta})}{\partial \boldsymbol{\theta}} \right|_{\boldsymbol{\theta}=\boldsymbol{\theta}_0}$$

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

$$\frac{\partial \ln p(\mathbf{x}; A)}{\partial A} = \frac{1}{\sigma^2} \sum_{n=0}^{N-1} (x[n] - A) \Rightarrow \left. \frac{\partial \ln p(\mathbf{x}; A)}{\partial A} \right|_{A=0} = \frac{N\bar{x}}{\sigma^2}$$

$$\frac{\partial^2 \ln p(\mathbf{x}; A)}{\partial A^2} = -\frac{N}{\sigma^2} \Rightarrow \mathbf{I}(\boldsymbol{\theta}_0) = \left\{ E \left( -\frac{\partial^2 \ln p(\mathbf{x}; A)}{\partial A^2} \right) \right\} \Big|_{A=0} = \frac{N}{\sigma^2}$$

✓ 对线性模型，  
GLRT、Wald、  
Rao的检验统计  
量是相同的

$$\left. \begin{array}{l} \Rightarrow T_R(\mathbf{x}) = \frac{N\bar{x}^2}{\sigma^2} \\ \Rightarrow T'_R(\mathbf{x}) = \bar{x}^2 \end{array} \right\}$$

例：非高斯噪声中未知信号检测——Rao检验

$$H_0 : x[n] = w[n]$$

$$H_1 : x[n] = A + w[n]$$

其中信号电平  $A (-\infty < A < +\infty)$  是未知的。噪声  $w[n]$  是独立同分布的，服从均值为零、方差为  $\sigma^2$  的广义高斯分布，其PDF为：

$$p(w[n]) = \frac{1}{a\sigma\Gamma\left(\frac{5}{4}\right)2^{\frac{5}{4}}} \exp\left\{-\frac{1}{2}\left(\frac{w[n]}{a\sigma}\right)^4\right\}, -\infty < w[n] < +\infty$$

其中常数为

$$a = \left( \frac{\Gamma\left(\frac{1}{4}\right)}{\sqrt{2}\Gamma\left(\frac{3}{4}\right)} \right)^{\frac{1}{2}} = 1.4464$$



$$p(w[n]) = \frac{1}{a\sigma\Gamma\left(\frac{5}{4}\right)2^{\frac{5}{4}}} \exp\left\{-\frac{1}{2}\left(\frac{w[n]}{a\sigma}\right)^4\right\}, -\infty < w[n] < +\infty$$

➡ 
$$p(\mathbf{x}; A) = \left( \frac{1}{a\sigma\Gamma\left(\frac{5}{4}\right)2^{\frac{5}{4}}} \right)^N \exp\left\{-\frac{1}{2}\sum_{n=0}^{N-1}\left(\frac{x[n]-A}{a\sigma}\right)^4\right\}$$

➡ 
$$\ln p(\mathbf{x}; A) = -N \ln\left(a\sigma\Gamma\left(\frac{5}{4}\right)2^{\frac{5}{4}}\right) - \frac{1}{2}\sum_{n=0}^{N-1}\left(\frac{x[n]-A}{a\sigma}\right)^4$$

➡ 
$$\frac{\partial \ln p(\mathbf{x}; A)}{\partial A} = \frac{2}{a\sigma} \sum_{n=0}^{N-1} \left(\frac{x[n]-A}{a\sigma}\right)^3$$

MLE:  $\frac{\partial \ln p(\mathbf{x}; A)}{\partial A} = 0 \quad \hat{A} = ? \quad \text{难以求解!}$

$$\text{Rao检验: } T_R(\mathbf{x}) = \left( \left. \frac{\partial \ln p(\mathbf{x}; \boldsymbol{\theta})}{\partial \boldsymbol{\theta}} \right|_{\boldsymbol{\theta}=\boldsymbol{\theta}_0} \right)^T \mathbf{I}^{-1}(\boldsymbol{\theta}_0) \left. \frac{\partial \ln p(\mathbf{x}; \boldsymbol{\theta})}{\partial \boldsymbol{\theta}} \right|_{\boldsymbol{\theta}=\boldsymbol{\theta}_0}$$

$$\frac{\partial \ln p(\mathbf{x}; A)}{\partial A} = \frac{2}{a\sigma} \sum_{n=0}^{N-1} \left( \frac{x[n] - A}{a\sigma} \right)^3 \quad \Rightarrow$$

$$\left. \frac{\partial \ln p(\mathbf{x}; A)}{\partial A} \right|_{A=0} = \frac{2}{a\sigma} \sum_{n=0}^{N-1} \left( \frac{x[n] - A}{a\sigma} \right)^3 \Big|_{A=0} = \frac{2}{a^4 \sigma^4} \sum_{n=0}^{N-1} x^3[n]$$

$$\frac{\partial^2 \ln p(\mathbf{x}; A)}{\partial A^2} = -\frac{6}{a^2 \sigma^2} \sum_{n=0}^{N-1} \left( \frac{x[n] - A}{a\sigma} \right)^2 \quad \Rightarrow$$

$$\mathbf{I}(\boldsymbol{\theta}) = \mathbf{I}(A) = E \left( -\frac{\partial^2 \ln p(\mathbf{x}; A)}{\partial A^2} \right) = \frac{6}{a^2 \sigma^2} \sum_{n=0}^{N-1} E \left( \left( \frac{x[n] - A}{a\sigma} \right)^2 \right) = \frac{6N}{a^4 \sigma^2}$$

$$\Rightarrow T_R(\mathbf{x}) = \frac{2N}{3a^4 \sigma^6} \left( \frac{1}{N} \sum_{n=0}^{N-1} x^3[n] \right)^2$$

# ● 存在多余参数时Wald检验与Rao检验

假设检验模型（存在多余参数）

$$\begin{aligned} H_0 : \boldsymbol{\theta}_r &= \boldsymbol{\theta}_{r_0}, \boldsymbol{\theta}_s \\ H_1 : \boldsymbol{\theta}_r &\neq \boldsymbol{\theta}_{r_0}, \boldsymbol{\theta}_s \quad (\boldsymbol{\theta}_{r_1} \approx \boldsymbol{\theta}_{r_0}) \end{aligned}$$

$\boldsymbol{\theta}_s$  是多余且未知的参数

Wald检验: 
$$T_W(\mathbf{x}) = (\hat{\boldsymbol{\theta}}_{r_1} - \boldsymbol{\theta}_{r_0})^T \left( \left[ \mathbf{I}^{-1}(\hat{\boldsymbol{\theta}}_1) \right]_{\boldsymbol{\theta}_r, \boldsymbol{\theta}_r} \right)^{-1} (\hat{\boldsymbol{\theta}}_{r_1} - \boldsymbol{\theta}_{r_0})$$

其中  $\hat{\boldsymbol{\theta}}_1 = [\hat{\boldsymbol{\theta}}_{r_1}^T, \hat{\boldsymbol{\theta}}_{s_1}^T]^T$  是  $\boldsymbol{\theta}$  在  $H_1$  下的MLE,  $[\mathbf{I}^{-1}(\boldsymbol{\theta})]_{\boldsymbol{\theta}_r, \boldsymbol{\theta}_r}$  是  $\mathbf{I}^{-1}(\boldsymbol{\theta})$  的左上分块矩阵,

$$[\mathbf{I}^{-1}(\boldsymbol{\theta})]_{\boldsymbol{\theta}_r, \boldsymbol{\theta}_r} = (\mathbf{I}_{\boldsymbol{\theta}_r, \boldsymbol{\theta}_r}(\boldsymbol{\theta}) - \mathbf{I}_{\boldsymbol{\theta}_r, \boldsymbol{\theta}_s}(\boldsymbol{\theta}) \mathbf{I}_{\boldsymbol{\theta}_s, \boldsymbol{\theta}_s}^{-1}(\boldsymbol{\theta}) \mathbf{I}_{\boldsymbol{\theta}_s, \boldsymbol{\theta}_r}(\boldsymbol{\theta}))^{-1}$$

$$\mathbf{I}(\boldsymbol{\theta}) = \mathbf{I}(\boldsymbol{\theta}_r, \boldsymbol{\theta}_s) = \begin{bmatrix} \mathbf{I}_{\boldsymbol{\theta}_r, \boldsymbol{\theta}_r}(\boldsymbol{\theta}_r, \boldsymbol{\theta}_s) & \mathbf{I}_{\boldsymbol{\theta}_r, \boldsymbol{\theta}_s}(\boldsymbol{\theta}_r, \boldsymbol{\theta}_s) \\ \mathbf{I}_{\boldsymbol{\theta}_s, \boldsymbol{\theta}_r}(\boldsymbol{\theta}_r, \boldsymbol{\theta}_s) & \mathbf{I}_{\boldsymbol{\theta}_s, \boldsymbol{\theta}_s}(\boldsymbol{\theta}_r, \boldsymbol{\theta}_s) \end{bmatrix}$$

前提条件:

- 双边检测
- 弱信号
- 大数据量
- 相同pdf形式

(推导见附录6B)

假设检验模型（存在多余参数）

$$\begin{aligned} H_0 : \boldsymbol{\theta}_r &= \boldsymbol{\theta}_{r_0}, \boldsymbol{\theta}_s \\ H_1 : \boldsymbol{\theta}_r &\neq \boldsymbol{\theta}_{r_0}, \boldsymbol{\theta}_s \end{aligned} \quad (\boldsymbol{\theta}_{r_1} \approx \boldsymbol{\theta}_{r_0})$$

$\boldsymbol{\theta}_s$  是多余且未知的参数

$$\text{Rao检验: } T_R(\mathbf{x}) = \left( \left. \frac{\partial \ln p(\mathbf{x}; \boldsymbol{\theta})}{\partial \boldsymbol{\theta}_r} \right|_{\boldsymbol{\theta} = \tilde{\boldsymbol{\theta}}} \right)^T \left[ \mathbf{I}^{-1}(\tilde{\boldsymbol{\theta}}) \right]_{\boldsymbol{\theta}_r \boldsymbol{\theta}_r} \left. \frac{\partial \ln p(\mathbf{x}; \boldsymbol{\theta})}{\partial \boldsymbol{\theta}_r} \right|_{\boldsymbol{\theta} = \tilde{\boldsymbol{\theta}}}$$

其中  $\tilde{\boldsymbol{\theta}} = [\boldsymbol{\theta}_{r_0}^T, \hat{\boldsymbol{\theta}}_{s_0}^T]^T$  是  $\boldsymbol{\theta}$  在  $H_0$  下的MLE,  $[\mathbf{I}^{-1}(\boldsymbol{\theta})]_{\boldsymbol{\theta}_r \boldsymbol{\theta}_r}$  是  $\mathbf{I}^{-1}(\boldsymbol{\theta})$  的左上分块矩阵,

$$[\mathbf{I}^{-1}(\boldsymbol{\theta})]_{\boldsymbol{\theta}_r \boldsymbol{\theta}_r} = \left( \mathbf{I}_{\boldsymbol{\theta}_r \boldsymbol{\theta}_r}(\boldsymbol{\theta}) - \mathbf{I}_{\boldsymbol{\theta}_r \boldsymbol{\theta}_s}(\boldsymbol{\theta}) \mathbf{I}_{\boldsymbol{\theta}_s \boldsymbol{\theta}_s}^{-1}(\boldsymbol{\theta}) \mathbf{I}_{\boldsymbol{\theta}_s \boldsymbol{\theta}_r}(\boldsymbol{\theta}) \right)^{-1}$$

$$\mathbf{I}(\boldsymbol{\theta}) = \mathbf{I}(\boldsymbol{\theta}_r, \boldsymbol{\theta}_s) = \begin{bmatrix} \mathbf{I}_{\boldsymbol{\theta}_r \boldsymbol{\theta}_r}(\boldsymbol{\theta}_r, \boldsymbol{\theta}_s) & \mathbf{I}_{\boldsymbol{\theta}_r \boldsymbol{\theta}_s}(\boldsymbol{\theta}_r, \boldsymbol{\theta}_s) \\ \mathbf{I}_{\boldsymbol{\theta}_s \boldsymbol{\theta}_r}(\boldsymbol{\theta}_r, \boldsymbol{\theta}_s) & \mathbf{I}_{\boldsymbol{\theta}_s \boldsymbol{\theta}_s}(\boldsymbol{\theta}_r, \boldsymbol{\theta}_s) \end{bmatrix}$$

前提条件:

- 双边检测
- 弱信号
- 大数据量
- 相同pdf形式

(推导见附录6B)

## 二、大数据量时GLRT的性能

GLRT检验统计量:

$$L_G(\mathbf{x}) = \frac{p(\mathbf{x}; \hat{\boldsymbol{\theta}}_1)}{p(\mathbf{x}; \boldsymbol{\theta}_0)} \quad \text{ROC?}$$

$$P_{FA} = \Pr(L_G(\mathbf{x}) > \gamma; H_0)$$

$$P_D = \Pr(L_G(\mathbf{x}) > \gamma; H_1)$$

### 1. 无多余参数时

$$H_0: \boldsymbol{\theta} = \boldsymbol{\theta}_0$$

$$H_1: \boldsymbol{\theta} \neq \boldsymbol{\theta}_0 \quad (\boldsymbol{\theta}_1 \approx \boldsymbol{\theta}_0)$$

GLRT检验统计量

$$L_G(\mathbf{x}) = \frac{p(\mathbf{x}; \hat{\boldsymbol{\theta}}_1)}{p(\mathbf{x}; \boldsymbol{\theta}_0)}$$

大数据量时



Wald检验统计量

$$2 \ln L_G(\mathbf{x}) = (\hat{\boldsymbol{\theta}}_1 - \boldsymbol{\theta}_0)^T \mathbf{I}(\hat{\boldsymbol{\theta}}_1) (\hat{\boldsymbol{\theta}}_1 - \boldsymbol{\theta}_0)$$

$$2\ln L_G(\mathbf{x}) = (\hat{\boldsymbol{\theta}}_1 - \boldsymbol{\theta}_0)^T \mathbf{I}(\hat{\boldsymbol{\theta}}_1) (\hat{\boldsymbol{\theta}}_1 - \boldsymbol{\theta}_0)$$

当  $N \rightarrow \infty$  时

$$\hat{\boldsymbol{\theta}}_1 \overset{a}{\sim} \begin{cases} N(\boldsymbol{\theta}_0, \mathbf{I}^{-1}(\boldsymbol{\theta}_0)), & H_0 \\ N(\boldsymbol{\theta}_1, \mathbf{I}^{-1}(\boldsymbol{\theta}_1)), & H_1 \end{cases} \quad \Rightarrow \quad \hat{\boldsymbol{\theta}}_1 - \boldsymbol{\theta}_0 \overset{a}{\sim} \begin{cases} N(\mathbf{0}, \mathbf{I}^{-1}(\boldsymbol{\theta}_0)), & H_0 \\ N(\boldsymbol{\theta}_1 - \boldsymbol{\theta}_0, \mathbf{I}^{-1}(\boldsymbol{\theta}_1)), & H_1 \end{cases}$$

若  $\mathbf{x} \sim N(\boldsymbol{\mu}, \mathbf{C})$ , 那么  $y = \mathbf{x}^T \mathbf{C}^{-1} \mathbf{x}$  服从如下非中心chi方分布

$$y \sim \chi_n^2(\lambda)$$

其中非中心参量  $\lambda = \boldsymbol{\mu}^T \mathbf{C}^{-1} \boldsymbol{\mu}$ 。

$H_1$  时, 当  $N \rightarrow \infty$ ,  $\hat{\boldsymbol{\theta}}_1 \rightarrow \boldsymbol{\theta}_1 \approx \boldsymbol{\theta}_0$

$$H_1 \text{ 时, } 2\ln L_G(\mathbf{x}) \rightarrow (\hat{\boldsymbol{\theta}}_1 - \boldsymbol{\theta}_0)^T \mathbf{I}(\boldsymbol{\theta}_1) (\hat{\boldsymbol{\theta}}_1 - \boldsymbol{\theta}_0) \overset{a}{\sim} \chi_p^2(\lambda), \lambda = (\boldsymbol{\theta}_1 - \boldsymbol{\theta}_0)^T \mathbf{I}(\boldsymbol{\theta}_1) (\boldsymbol{\theta}_1 - \boldsymbol{\theta}_0) \\ = (\boldsymbol{\theta}_1 - \boldsymbol{\theta}_0)^T \mathbf{I}(\boldsymbol{\theta}_0) (\boldsymbol{\theta}_1 - \boldsymbol{\theta}_0)$$

$$H_0 \text{ 时, } 2\ln L_G(\mathbf{x}) \rightarrow (\hat{\boldsymbol{\theta}}_1 - \boldsymbol{\theta}_0)^T \mathbf{I}(\boldsymbol{\theta}_0) (\hat{\boldsymbol{\theta}}_1 - \boldsymbol{\theta}_0) \overset{a}{\sim} \chi_p^2(0)$$

例：WGN中未知信号检测

$$H_0 : x[n] = w[n]$$

$$H_1 : x[n] = A + w[n]$$

其中信号电平  $A$  ( $-\infty < A < +\infty$ ) 是未知的。噪声  $w[n]$  是方差为  $\sigma^2$  的WGN。GLRT检测统计量的性能？

$$\text{GLRT检测统计量: } 2\ln L_G(\mathbf{x}) = \frac{N\bar{x}^2}{\sigma^2} \quad (\text{见第十三章P21})$$

$$H_1 \text{ 时, } 2\ln L_G(\mathbf{x}) \rightarrow (\boldsymbol{\theta}_1 - \boldsymbol{\theta}_0)^T \mathbf{I}(\boldsymbol{\theta}_1)(\boldsymbol{\theta}_1 - \boldsymbol{\theta}_0) \stackrel{a}{\sim} \chi_p^2(\lambda), \lambda = (\boldsymbol{\theta}_1 - \boldsymbol{\theta}_0)^T \mathbf{I}(\boldsymbol{\theta}_0)(\boldsymbol{\theta}_1 - \boldsymbol{\theta}_0)$$

$$H_0 \text{ 时, } 2\ln L_G(\mathbf{x}) \rightarrow (\boldsymbol{\theta}_0 - \boldsymbol{\theta}_0)^T \mathbf{I}(\boldsymbol{\theta}_0)(\boldsymbol{\theta}_0 - \boldsymbol{\theta}_0) \stackrel{a}{\sim} \chi_p^2(0)$$

$$\boldsymbol{\theta}_1 = A, \quad \boldsymbol{\theta}_0 = 0, \quad \mathbf{I}(\boldsymbol{\theta}_0) = \frac{N}{\sigma^2} \quad \Rightarrow$$

✓ 对线性模型，渐近统计特性对有限数据记录是有效、且精确的

$$2\ln L_G(\mathbf{x}) \stackrel{a}{\sim} \begin{cases} \chi_1^2(0), & H_0 \\ \chi_1^2\left(\frac{NA^2}{\sigma^2}\right), & H_1 \end{cases}, \text{ 且进一步有 } 2\ln L_G(\mathbf{x}) \sim \begin{cases} \chi_1^2(0), & H_0 \\ \chi_1^2\left(\frac{NA^2}{\sigma^2}\right), & H_1 \end{cases}$$

## 2. 存在多余参数时

$$H_0: \boldsymbol{\theta}_r = \boldsymbol{\theta}_{r_0}, \boldsymbol{\theta}_s$$

$$H_1: \boldsymbol{\theta}_r \neq \boldsymbol{\theta}_{r_0}, \boldsymbol{\theta}_s \quad (\boldsymbol{\theta}_{r_1} \approx \boldsymbol{\theta}_{r_0})$$

$\boldsymbol{\theta}_s$  是多余且未知的参数

$$2\ln L_G(\mathbf{x}) \overset{a}{\sim} \begin{cases} \chi_r^2(0), & H_0 \\ \chi_r^2(\lambda), & H_1 \end{cases}$$

其中，非中心参量

$$\lambda = (\boldsymbol{\theta}_{r_1} - \boldsymbol{\theta}_{r_0})^T \left[ \mathbf{I}_{\boldsymbol{\theta}_r \boldsymbol{\theta}_r}(\boldsymbol{\theta}_{r_0}, \boldsymbol{\theta}_s) - \mathbf{I}_{\boldsymbol{\theta}_r \boldsymbol{\theta}_s}(\boldsymbol{\theta}_{r_0}, \boldsymbol{\theta}_s) \mathbf{I}_{\boldsymbol{\theta}_s \boldsymbol{\theta}_s}^{-1}(\boldsymbol{\theta}_{r_0}, \boldsymbol{\theta}_s) \mathbf{I}_{\boldsymbol{\theta}_s \boldsymbol{\theta}_r}(\boldsymbol{\theta}_{r_0}, \boldsymbol{\theta}_s) \right] (\boldsymbol{\theta}_{r_1} - \boldsymbol{\theta}_{r_0})$$

Fisher信息矩阵为

$$\mathbf{I}(\boldsymbol{\theta}) = \mathbf{I}(\boldsymbol{\theta}_r, \boldsymbol{\theta}_s) = \begin{bmatrix} \mathbf{I}_{\boldsymbol{\theta}_r \boldsymbol{\theta}_r}(\boldsymbol{\theta}_r, \boldsymbol{\theta}_s) & \mathbf{I}_{\boldsymbol{\theta}_r \boldsymbol{\theta}_s}(\boldsymbol{\theta}_r, \boldsymbol{\theta}_s) \\ \mathbf{I}_{\boldsymbol{\theta}_s \boldsymbol{\theta}_r}(\boldsymbol{\theta}_r, \boldsymbol{\theta}_s) & \mathbf{I}_{\boldsymbol{\theta}_s \boldsymbol{\theta}_s}(\boldsymbol{\theta}_r, \boldsymbol{\theta}_s) \end{bmatrix} \quad (\text{推导见附录6C})$$



# 三、局部最大势检测

单边检验:

$$\begin{cases} H_0 : \theta = \theta_0 \\ H_1 : \theta > \theta_0 \end{cases} \quad (\theta_1 \approx \theta_0) \text{ 弱信号}$$

采用NP准则，若似然比

$$L(\mathbf{x}) = \frac{p(\mathbf{x}; \theta, H_1)}{p(\mathbf{x}; \theta_0, H_0)} > \gamma \quad \text{简记为: } L(\mathbf{x}) = \frac{p(\mathbf{x}; \theta)}{p(\mathbf{x}; \theta_0)} > \gamma$$

则判  $H_1$

$$L(\mathbf{x}) = \frac{p(\mathbf{x}; \theta)}{p(\mathbf{x}; \theta_0)} > \gamma \quad \longleftrightarrow \quad \ln p(\mathbf{x}; \theta) - \ln p(\mathbf{x}; \theta_0) > \ln \gamma$$

$$\ln p(\mathbf{x}; \theta) = \ln p(\mathbf{x}; \theta_0) + \left. \frac{\partial \ln p(\mathbf{x}; \theta)}{\partial \theta} \right|_{\theta=\theta_0} (\theta - \theta_0)$$

$$\Rightarrow \left. \frac{\partial \ln p(\mathbf{x}; \theta)}{\partial \theta} \right|_{\theta=\theta_0} (\theta - \theta_0) > \ln \gamma$$

由于  $\theta > \theta_0$

$$\left. \frac{\partial \ln p(\mathbf{x}; \theta)}{\partial \theta} \right|_{\theta=\theta_0} > \frac{\ln \gamma}{\theta - \theta_0} = \gamma'$$

$$T_{LMP}(\mathbf{x}) = \frac{\left. \frac{\partial \ln p(\mathbf{x}; \theta)}{\partial \theta} \right|_{\theta=\theta_0}}{\sqrt{I(\theta_0)}} > \frac{\ln \gamma}{\sqrt{I(\theta_0)} (\theta - \theta_0)} = \gamma''$$

**局部最大势 (Locally Most Powerful, LMP) 检验**

## ● 大数据量时LMP的性能

$$\text{检测统计量: } T_{LMP}(\mathbf{x}) = \frac{\left. \frac{\partial \ln p(\mathbf{x}; \theta)}{\partial \theta} \right|_{\theta=\theta_0}}{\sqrt{I(\theta_0)}}$$

若观测数据是IID的,

$$\ln p(\mathbf{x}; \theta) = \sum_{n=0}^{N-1} \ln p(x[n]; \theta)$$

$$\Rightarrow \left. \frac{\partial \ln p(\mathbf{x}; \theta)}{\partial \theta} \right|_{\theta=\theta_0} = \sum_{n=0}^{N-1} \left. \frac{\partial \ln p(x[n]; \theta)}{\partial \theta} \right|_{\theta=\theta_0} \stackrel{a}{\sim} N(\mu_{LMP}, \sigma_{LMP}^2) \quad (\text{中心极限定理})$$

● 在  $H_0$  条件下

$$E \left( \left. \frac{\partial \ln p(\mathbf{x}; \theta)}{\partial \theta} \right|_{\theta=\theta_0} \right) = 0$$

$$\text{var} \left( \left. \frac{\partial \ln p(\mathbf{x}; \theta)}{\partial \theta} \right|_{\theta=\theta_0} \right) = E \left\{ \left( \left. \frac{\partial \ln p(\mathbf{x}; \theta)}{\partial \theta} \right|_{\theta=\theta_0} - \underbrace{E \left( \left. \frac{\partial \ln p(\mathbf{x}; \theta)}{\partial \theta} \right|_{\theta=\theta_0} \right)}_{=0} \right)^2 \right\} = I(\theta_0)$$

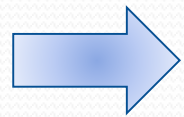
➡  $\left. \frac{\partial \ln p(\mathbf{x}; \theta)}{\partial \theta} \right|_{\theta=\theta_0} \overset{a}{\sim} N(0, I(\theta_0))$

➡  $\frac{\left. \frac{\partial \ln p(\mathbf{x}; \theta)}{\partial \theta} \right|_{\theta=\theta_0}}{\sqrt{I(\theta_0)}} \overset{a}{\sim} N(0, 1)$

● 在  $H_1$  条件下  $E \left( \left. \frac{\partial \ln p(\mathbf{x}; \theta)}{\partial \theta} \right|_{\theta=\theta_0} \right) ? = 0 ?$

$$\left. \frac{\partial \ln p(\mathbf{x}; \theta)}{\partial \theta} \right|_{\theta=\theta_0} = \left. \frac{\partial \ln p(\mathbf{x}; \theta)}{\partial \theta} \right|_{\theta=\theta_1} + \left. \frac{\partial^2 \ln p(\mathbf{x}; \theta)}{\partial \theta^2} \right|_{\theta=\theta_1} (\theta_0 - \theta_1)$$

$$E\left(\frac{\partial \ln p(\mathbf{x};\theta)}{\partial \theta}\bigg|_{\theta=\theta_0}\right) = \underbrace{E\left(\frac{\partial \ln p(\mathbf{x};\theta)}{\partial \theta}\bigg|_{\theta=\theta_1}\right)}_{=0} + E\left(\frac{\partial^2 \ln p(\mathbf{x};\theta)}{\partial \theta^2}\bigg|_{\theta=\theta_1}\right)(\theta_0 - \theta_1)$$



$$E\left(\frac{\partial \ln p(\mathbf{x};\theta)}{\partial \theta}\bigg|_{\theta=\theta_0}\right) = -I(\theta_1)(\theta_0 - \theta_1)$$

$$\text{var}\left(\frac{\partial \ln p(\mathbf{x};\theta)}{\partial \theta}\bigg|_{\theta=\theta_0}\right) = E\left\{\left(\frac{\partial \ln p(\mathbf{x};\theta)}{\partial \theta}\bigg|_{\theta=\theta_0} - E\left(\frac{\partial \ln p(\mathbf{x};\theta)}{\partial \theta}\bigg|_{\theta=\theta_0}\right)\right)^2\right\}$$

$$\frac{\partial \ln p(\mathbf{x};\theta)}{\partial \theta}\bigg|_{\theta=\theta_0} = \frac{\partial \ln p(\mathbf{x};\theta)}{\partial \theta}\bigg|_{\theta=\theta_1} + \frac{\partial^2 \ln p(\mathbf{x};\theta)}{\partial \theta^2}\bigg|_{\theta=\theta_1}(\theta_0 - \theta_1)$$

$$\text{var}\left(\frac{\partial \ln p(\mathbf{x};\theta)}{\partial \theta}\bigg|_{\theta=\theta_0}\right) = E\left\{\left(\frac{\partial \ln p(\mathbf{x};\theta)}{\partial \theta}\bigg|_{\theta=\theta_1} + \left(\frac{\partial^2 \ln p(\mathbf{x};\theta)}{\partial \theta^2}\bigg|_{\theta=\theta_1} + I(\theta_1)\right)(\theta_0 - \theta_1)\right)^2\right\}$$

$$\text{var} \left( \left. \frac{\partial \ln p(\mathbf{x}; \theta)}{\partial \theta} \right|_{\theta=\theta_0} \right) = E \left\{ \begin{aligned} & \left( \left. \frac{\partial \ln p(\mathbf{x}; \theta)}{\partial \theta} \right|_{\theta=\theta_1} \right)^2 + \left( \left. \frac{\partial^2 \ln p(\mathbf{x}; \theta)}{\partial \theta^2} \right|_{\theta=\theta_1} + I(\theta_1) \right)^2 (\theta_0 - \theta_1)^2 \\ & + 2 \left. \frac{\partial \ln p(\mathbf{x}; \theta)}{\partial \theta} \right|_{\theta=\theta_1} \left( \left. \frac{\partial^2 \ln p(\mathbf{x}; \theta)}{\partial \theta^2} \right|_{\theta=\theta_1} + I(\theta_1) \right) (\theta_0 - \theta_1) \end{aligned} \right\}$$

$$\approx E \left\{ \left( \left. \frac{\partial \ln p(\mathbf{x}; \theta)}{\partial \theta} \right|_{\theta=\theta_1} \right)^2 \right\} = I(\theta_1) \approx I(\theta_0)$$

$$\Rightarrow \left. \frac{\partial \ln p(\mathbf{x}; \theta)}{\partial \theta} \right|_{\theta=\theta_0} \overset{a}{\sim} N(-I(\theta_1)(\theta_0 - \theta_1), I(\theta_0))$$

$$\Rightarrow \left. \frac{\partial \ln p(\mathbf{x}; \theta)}{\partial \theta} \right|_{\theta=\theta_0} \overset{a}{\sim} N(I(\theta_0)(\theta_1 - \theta_0), I(\theta_0)) \Rightarrow \frac{\left. \frac{\partial \ln p(\mathbf{x}; \theta)}{\partial \theta} \right|_{\theta=\theta_0}}{\sqrt{I(\theta_0)}} \overset{a}{\sim} N(\sqrt{I(\theta_0)}(\theta_1 - \theta_0), 1)$$

因此，对大数据量：

$$T_{LMP}(\mathbf{x}) = \frac{\left. \frac{\partial \ln p(\mathbf{x}; \theta)}{\partial \theta} \right|_{\theta=\theta_0}}{\sqrt{I(\theta_0)}} \overset{a}{\sim} \begin{cases} N(0, 1), & H_0 \\ N(\sqrt{I(\theta_0)}(\theta_1 - \theta_0), 1), & H_1 \end{cases}$$

## 四、最小错误概率检测——广义ML准则

例：WGN中电平检测——多元假设检验

$$H_0 : x[n] = w[n]$$

$$H_1 : x[n] = A + w[n]$$

$$H_2 : x[n] = A + Bn + w[n]$$

噪声  $w[n]$  是方差为  $\sigma^2$  的WGN。 $A, B, \sigma^2$  是未知参数。采用最小错误概率准则时，应该如何检测？

最小错误  
概率准则/  
最大后验  
概率准则

$$\max_i p(H_i / \mathbf{x}) \xrightarrow{\text{先验相同时}} \max_i p(\mathbf{x} / H_i)$$

# GLRT?

NP准则下的GLRT:

$$\text{若 } L_G(\mathbf{x}) = \frac{\max_{\theta_1} p(\mathbf{x}; \theta_1, H_1)}{\max_{\theta_0} p(\mathbf{x}; \theta_0, H_0)} > \gamma$$

则判  $H_1$

推广至

$$\max_{\theta_i} p(\mathbf{x}; \theta_i | H_i)$$



$$\max_{\theta_i} \ln p(\mathbf{x}; \theta_i | H_i)$$

?



$$p(\mathbf{x}; A, B, \sigma^2) = \frac{1}{(2\pi\sigma^2)^{N/2}} \exp \left\{ -\frac{1}{2\sigma^2} \sum_{n=0}^{N-1} (x[n] - A - Bn)^2 \right\}$$

$$\max_{\theta_i} p(\mathbf{x}; \theta_i | H_i) \rightarrow \left\{ \begin{array}{l} H_0 : \max_{\sigma^2} p(\mathbf{x}; A=0, B=0, \sigma^2) \\ H_1 : \max_{A, \sigma^2} p(\mathbf{x}; A, B=0, \sigma^2) \\ H_2 : \max_{A, B, \sigma^2} p(\mathbf{x}; A, B, \sigma^2) \end{array} \right\} \rightarrow \text{总是判 } H_2$$



$$\max_{\theta_i} \ln p(\mathbf{x}; \theta_i | H_i) \quad \longrightarrow \quad \max_i \left\{ \ln p(\mathbf{x}; \hat{\theta}_i | H_i) - \frac{1}{2} \ln \left( \det(\mathbf{I}(\hat{\theta}_i)) \right) \right\}$$



修正项

或惩罚项(penalty term)

(推导见附录6F)

最小错误概率准则下（假定先验概率相同）检测：

$$\max_i \left\{ \ln p(\mathbf{x}; \hat{\theta}_i | H_i) - \frac{1}{2} \ln \left( \det(\mathbf{I}(\hat{\theta}_i)) \right) \right\}$$

广义ML  
准则

# 五、应用案例

## ● 卫星导航系统脆弱性



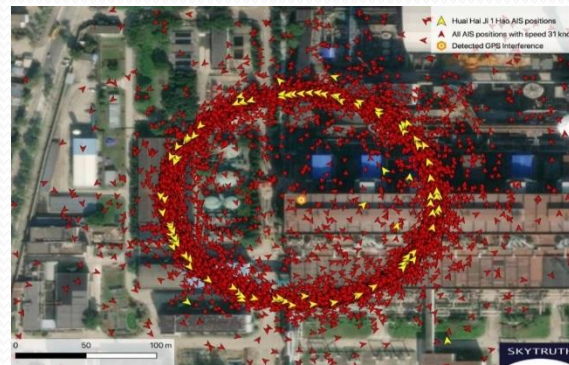
2011年

伊朗宣称通过GPS欺骗干扰在内的电子对抗手段，成功截获美中央情报局派出执行监控任务的哨兵无人侦查机



2013年

美德州大学奥斯汀分校Humphreys教授团队，成功对游艇开展了GPS欺骗攻击，使游艇偏出预定航线一公里



2019年

GPS “怪圈：一旦进入某区域，定位结果呈现“圆圈”形状

## 如何有效防御欺骗干扰？

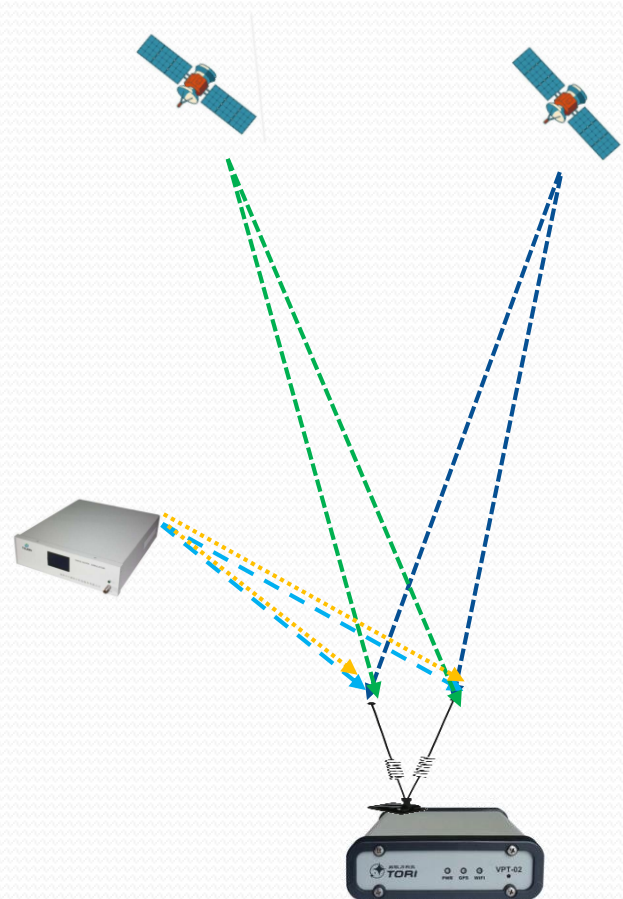
清华大学电子工程系 李洪 副教授

## ➤ 双天线载波相位双差欺骗检测技术

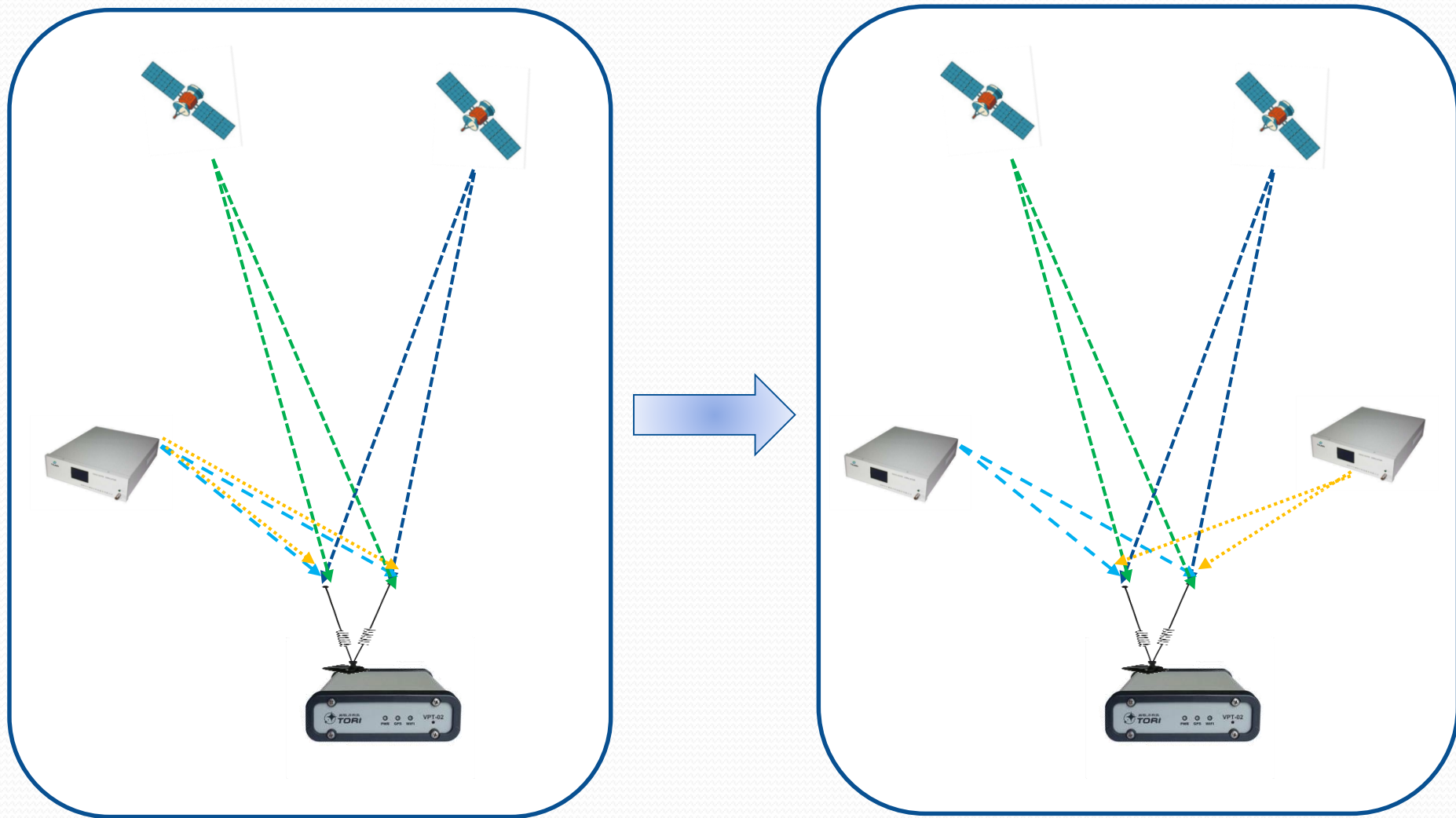
$$\begin{cases} H_0 : \nabla \Delta \varphi = w[n] \\ H_1 : \nabla \Delta \varphi = \theta + w[n] \end{cases}$$

### ——GLRT检测问题

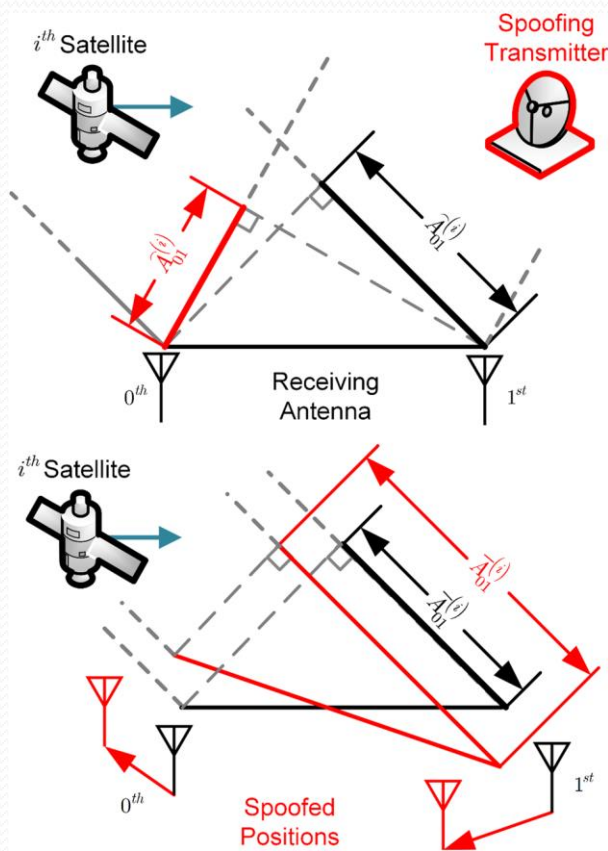
- Jafarnia A, etc, A double antenna approach toward detection, classification and mitigation of GNSS structural interference, Proceedings of NAVITEC 2014, ESA-ESTEC, Noordwijk, December 3–5
- Psiaki ML, et, GNSS spoofing detection using two-antenna differential carrier phase, Proceedings of the ION GNSS + 2014, September 8–12, pp 2776–2800
- Borio D, etc, A sum-of-squares approach to GNSS spoofing detection, IEEE Transactions on Aerospace and Electronics Systems, 2016, 52(4):1756–1768



## 失效场景

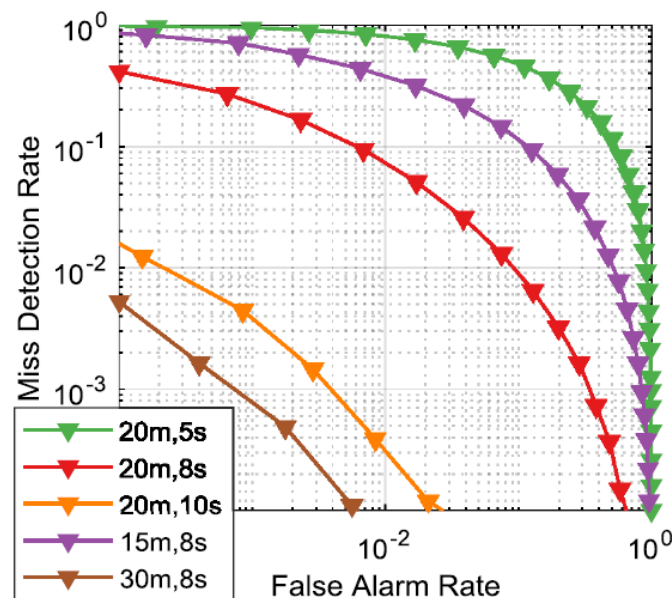


# 双天线到达频率差欺骗检测技术



$$\begin{cases} H_0 : \bar{A}_{01}^{(i)} - \hat{A}_{01}^{(i)} = 0 \\ H_1 : \bar{A}_{01}^{(i)} - \hat{A}_{01}^{(i)} \neq 0 \end{cases} \quad \text{——GLRT检测问题}$$

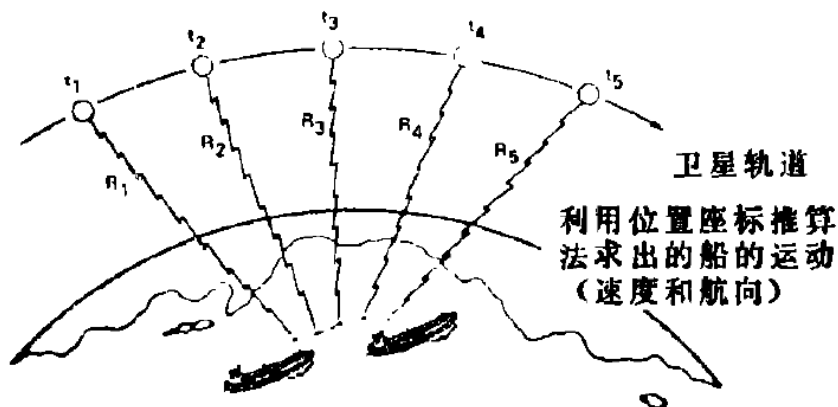
- 检测预测的单位时间内载波相位变化即多普勒，与实测值间是否一致



- Li He, Hong Li, Mingquan Lu, Dual-Antenna GNSS Spoofing Detection Method Based on Doppler Frequency Difference of Arrival, GPS Solutions, 2019 23:78, DOI: 10.1007/s10291-019-0868-5



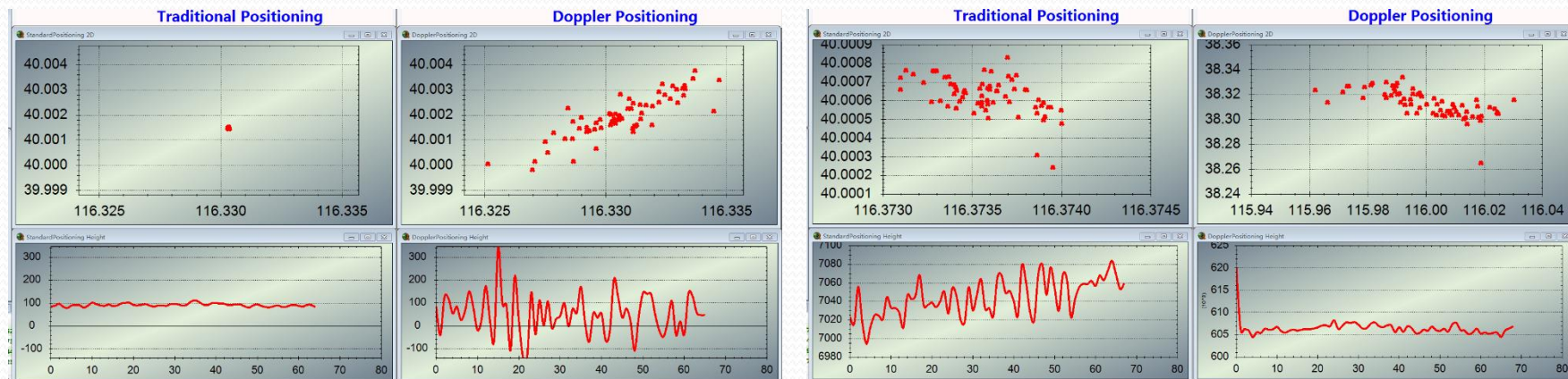
# 多普勒与伪距定位结果一致性欺骗检测技术



$$s[k] = \|\mathbf{P}^d[k] - \mathbf{P}^t[k]\|$$

$$\begin{cases} H_0 : s[k] = n[k] \\ H_1 : s[k] = d + n[k] \end{cases}$$

——GLRT检测问题



- Fengkui Chu, Hong Li, Jian Wen, Mingquan Lu, Statistical Model and Performance Evaluation for GNSS Spoofing Detection Method Based on the Consistency of Doppler and Pseudorange Positioning Results, Journal of Navigation, 2019, 72(2): 447-466

# 六、小结

- GLRT等效方法
  - 条件：双边、弱信号、大数据量
  - Wald检验、Rao检验
- GLRT的性能
  - 条件：双边、弱信号、大数据量
  - 渐近服从chi方分布；对Wald检验、Rao检验同样适用
- 单边检测时UMP的渐近方法：LMP
  - 条件：单边、标量、弱信号、无多余参数
  - 大数据量时，渐近服从高斯分布
- 最小错误概率准则下信号检测
  - GLRT不再适用，需引入修正项
- GLRT方法的应用