

## 3.8 Vector Transformations

Just like for the scalar case....  $\alpha = g(\theta)$

If you know  $\text{CRLB}_\theta$  you can find  $\text{CRLB}_\alpha$

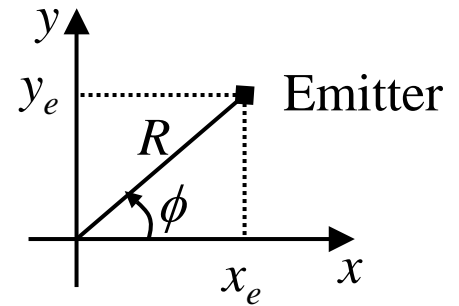
$$\text{CRLB}_\alpha = \underbrace{\left[ \frac{\partial g(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}} \right] \underbrace{\mathbf{I}^{-1}(\boldsymbol{\theta})}_{\text{CRLB on } \boldsymbol{\theta}} \left[ \frac{\partial g(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}} \right]^T}_{\text{CRLB on } \alpha}$$

Jacobian Matrix  
(see p. 46)

**Example:** Usually can estimate Range (R) and Bearing ( $\varphi$ ) directly  
But might really want emitter (x, y)

# Example of Vector Transform

Can estimate Range ( $R$ ) and Bearing ( $\phi$ ) directly  
 But might really want emitter location ( $x_e, y_e$ )



**Direct  
Parameters**

$$\boldsymbol{\theta} = \begin{bmatrix} R \\ \phi \end{bmatrix}$$

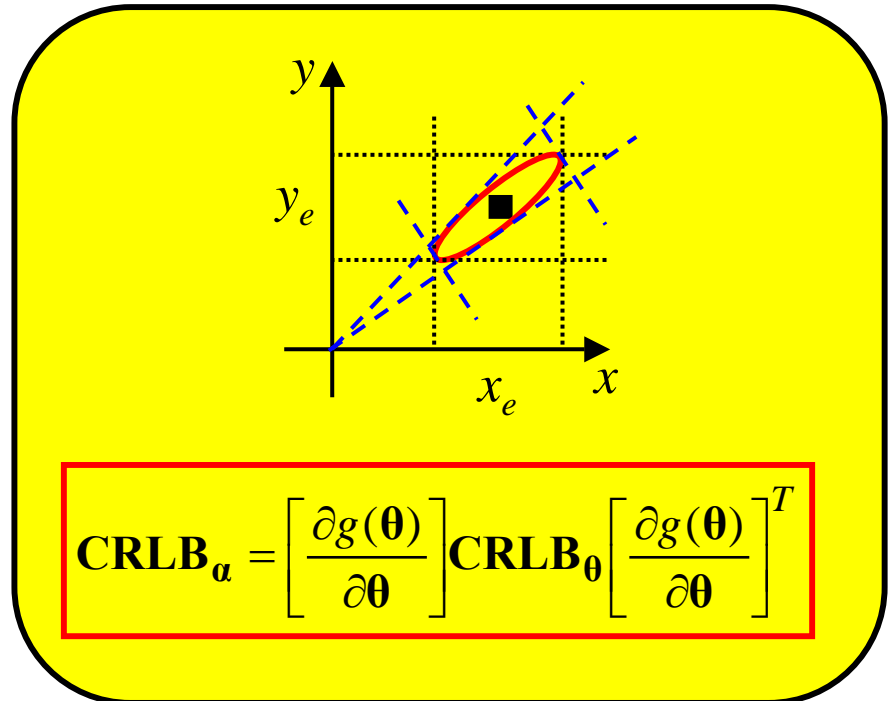
$$\boldsymbol{\alpha} = \begin{bmatrix} x_e \\ y_e \end{bmatrix} = g(\boldsymbol{\theta}) = \begin{bmatrix} R \cos \phi \\ R \sin \phi \end{bmatrix}$$

**Mapped  
Parameters**

**Jacobian Matrix**

$$\frac{\partial g(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}} = \begin{bmatrix} \frac{\partial R \cos \phi}{\partial R} & \frac{\partial R \cos \phi}{\partial \phi} \\ \frac{\partial R \sin \phi}{\partial R} & \frac{\partial R \sin \phi}{\partial \phi} \end{bmatrix}$$

$$= \begin{bmatrix} \cos \phi & -R \sin \phi \\ \sin \phi & R \cos \phi \end{bmatrix}$$



$$\text{CRLB}_{\boldsymbol{\alpha}} = \left[ \frac{\partial g(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}} \right] \text{CRLB}_{\boldsymbol{\theta}} \left[ \frac{\partial g(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}} \right]^T$$

## 3.9 CRLB for General Gaussian Case

In Sect. 3.5 we saw the CRLB for “signal + AWGN”

For that case we saw:

The PDF’s parameter-dependence showed up only in the mean of the PDF

Deterministic Signal w/  
Scalar Deterministic Parameter

Now generalize to the case where:

$$\mathbf{x} \sim N(\boldsymbol{\mu}(\boldsymbol{\theta}), \mathbf{C}(\boldsymbol{\theta}))$$

- Data is still Gaussian, but
- Parameter-Dependence not restricted to Mean
- Noise not restricted to White... Cov not necessarily diagonal

One way to get this case: “signal + AGN”

Random Gaussian Signal w/  
Vector Deterministic Parameter

Non-White Noise

For this case the FIM is given by: (See Appendix 3c)

$$[\mathbf{I}(\boldsymbol{\theta})]_{ij} = \underbrace{\left[ \frac{\partial \boldsymbol{\mu}(\boldsymbol{\theta})}{\partial \theta_i} \right]^T \mathbf{C}^{-1}(\boldsymbol{\theta}) \left[ \frac{\partial \boldsymbol{\mu}(\boldsymbol{\theta})}{\partial \theta_j} \right]}_{\text{Variability of Mean w.r.t. parameters}} + \frac{1}{2} \text{tr} \left[ \underbrace{\mathbf{C}^{-1}(\boldsymbol{\theta}) \frac{\partial \mathbf{C}(\boldsymbol{\theta})}{\partial \theta_i} \mathbf{C}^{-1}(\boldsymbol{\theta}) \frac{\partial \mathbf{C}(\boldsymbol{\theta})}{\partial \theta_j}}_{\text{Covariance Variability}} \right]$$

Variability of Mean  
w.r.t. parameters

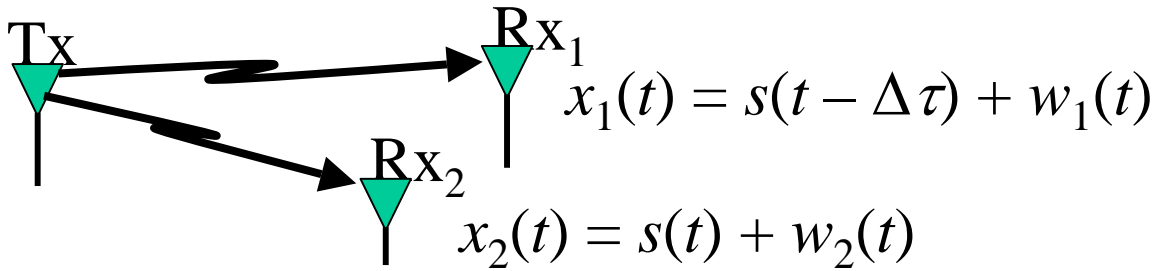
This shows the impact of signal model assumptions

- deterministic signal + AGN
- random Gaussian signal + AGN

Est. Cov. uses average  
over only noise

Est. Cov. uses average  
over signal & noise

# Gen. Gauss. Ex.: Time-Difference-of-Arrival



Given:

$$\mathbf{x} = \begin{bmatrix} \mathbf{x}_1^T & \mathbf{x}_2^T \end{bmatrix}^T$$

Goal: Estimate  $\Delta\tau$

## How to model the signal?

- Case #1:  $s(t)$  is zero-mean, WSS, Gauss. Process — **Passive Sonar**
- Case #2:  $s(t)$  is a deterministic signal — **Radar/Comm Location**

### Case #1

$\mu(\Delta\tau) = \mathbf{0} \implies$  **No Term #1**

$$\mathbf{C}(\Delta\tau) = \begin{bmatrix} \mathbf{C}_{11} & \mathbf{C}_{12}(\Delta\tau) \\ \mathbf{C}_{21}(\Delta\tau) & \mathbf{C}_{22} \end{bmatrix}$$

$$\mathbf{C}_{ii} = \mathbf{C}_{s_i s_i} + \mathbf{C}_{w_i w_i}$$

$$\mathbf{C}_{ij}(\Delta\tau) = \mathbf{C}_{s_i s_j}(\Delta\tau)$$

### Case #1

$\mathbf{C}(\Delta\tau) = \mathbf{C} \implies$  **No Term #2**

$$\mu(\Delta\tau) = \begin{bmatrix} s_1[0; \Delta\tau] \\ s_1[1; \Delta\tau] \\ \vdots \\ s_1[N-1; \Delta\tau] \\ s_2[0; \Delta\tau] \\ \vdots \\ s_2[N-1; \Delta\tau] \end{bmatrix}$$

# Comments on General Gaussian CRLB

It is interesting to note that for any given problem you may find each case used in the literature!!!

For example for the TDOA/FDOA estimation problem:

- Case #1 used by M. Wax in *IEEE Trans. Info Theory*, Sept. 1982
- Case #2 used by S. Stein in *IEEE Trans. Signal Proc.*, Aug. 1993

See also differences in the book's examples

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**We'll skip Section 3.10 and leave it as a reading assignment**