

Estimation en traitement d'antenne

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Sommaire

Introduction

Le traitement d'antenne et analyse spectrale

Les techniques d'estimation :

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- Sélection de l'ordre

- Erreur de modèle et calibration

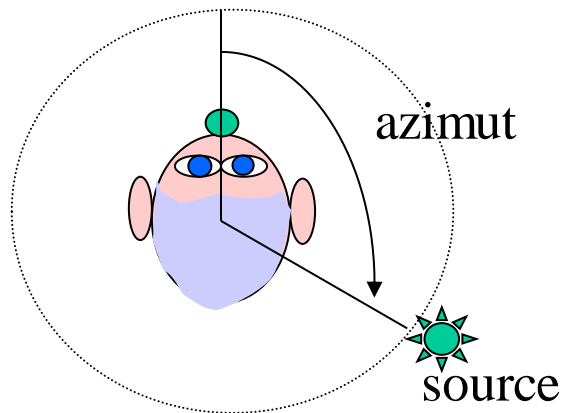
Radioastronomie

Géolocalisation

Localisation avec algorithmes parcimonieux

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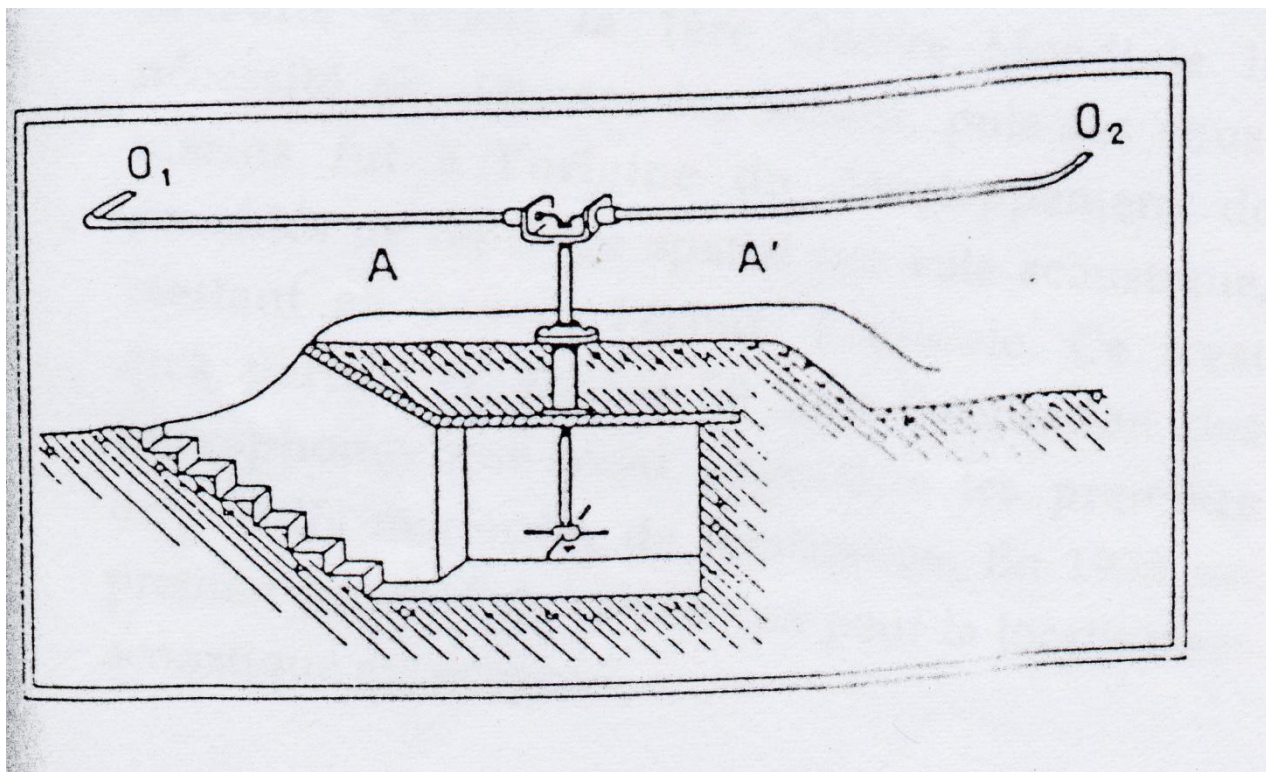
- Array signal processing

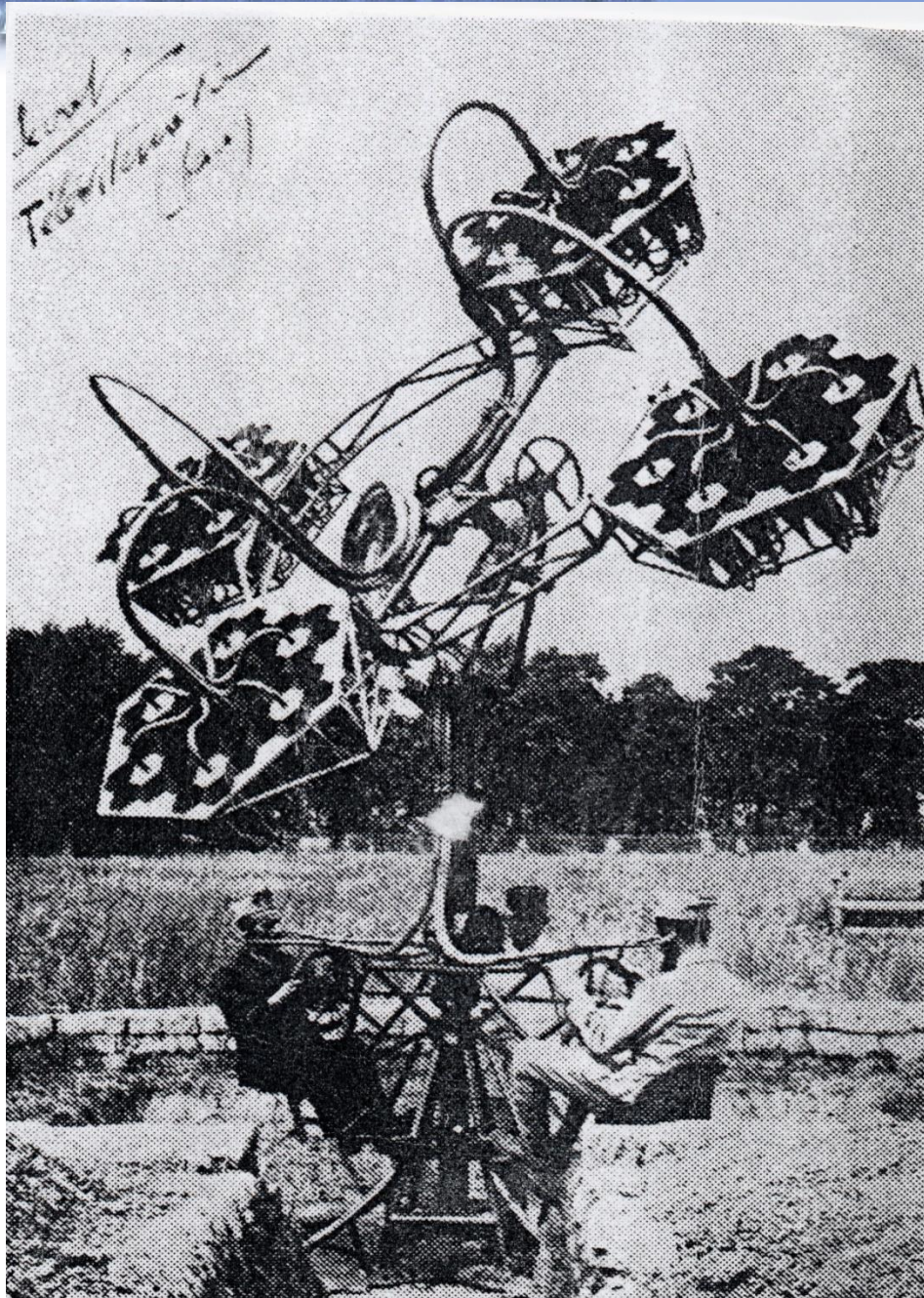


Sensibility in Azimut :

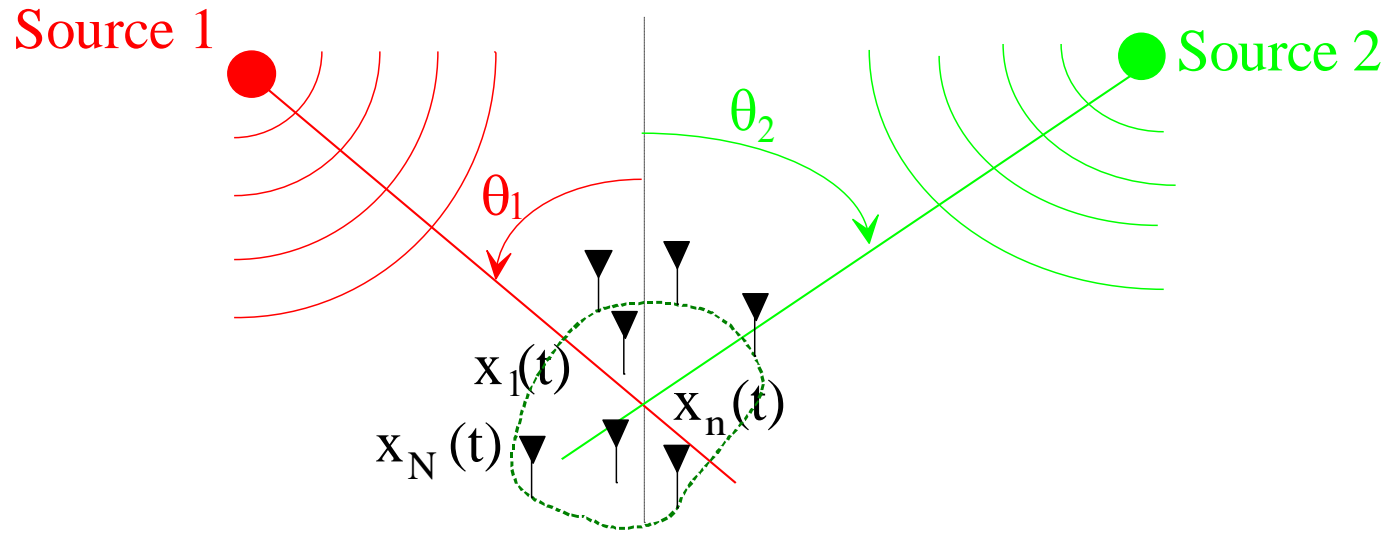
- phase and intensity







LE TRAITEMENT D'ANTENNE

**Estimation :**

- Localisation
- Détection
- Séparation
- Identification

$$\mathbf{x}(t) = \sum_{m=1}^M \mathbf{a}(\theta_m) \cdot s_m(t) + \mathbf{b}(t)$$

$$\mathbf{x}(t) = A(\theta) \cdot \mathbf{s}(t) + \mathbf{b}(t) = \mathbf{y}(t) + \mathbf{b}(t)$$

Two Types of Beamformers

- Method 1: Single sensor with directional response due to reflector, aperture size, baffles, pipes, etc.



Green Bank Telescope,
National Radio
Astronomy Observatory,
West Virginia.

100 m clear aperture.
Largest fully steerable
antenna in the world.

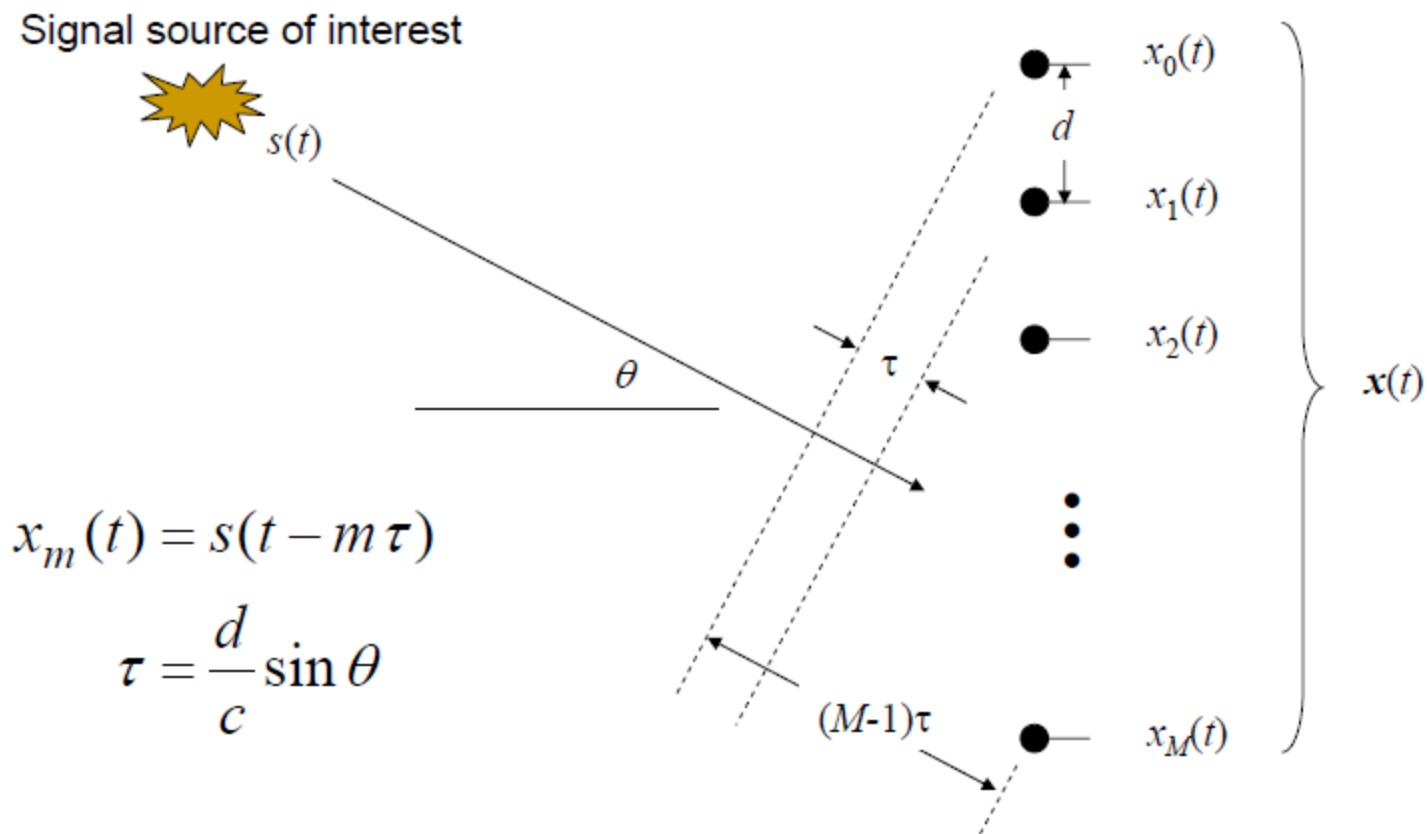
Two Types of Beamformers (cont.)

- Method 2: Sensor arrays. Used in SONAR, RADAR, communications, medical imaging, radio astronomy, etc.

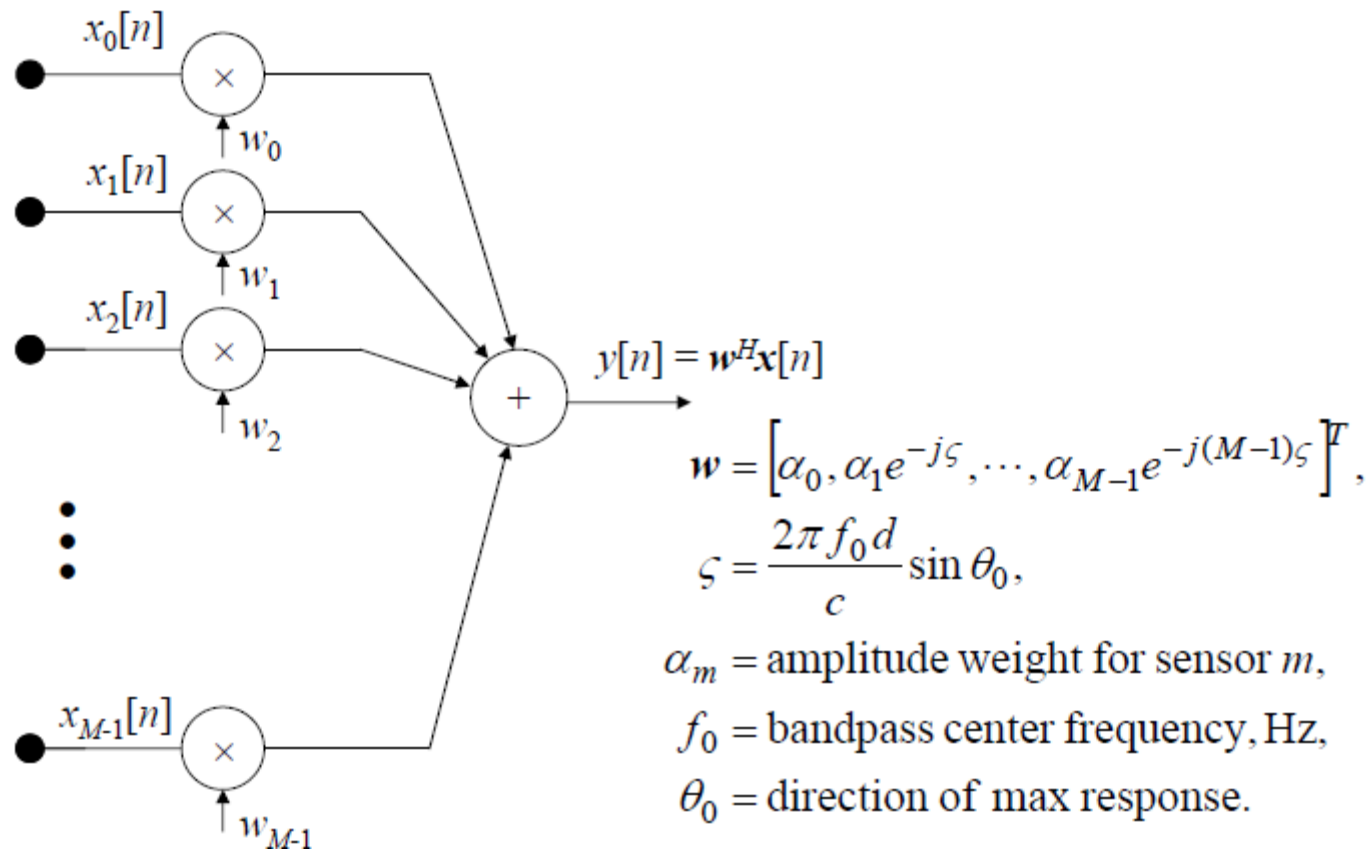


Line array of directional sensors
Westerbork Synthesis Array
Radio Telescope, (WSRT)
the Netherlands.

The Uniform Line Array

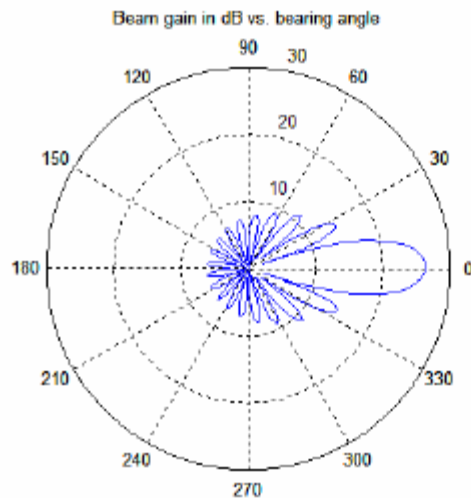


Narrowband Phased Array

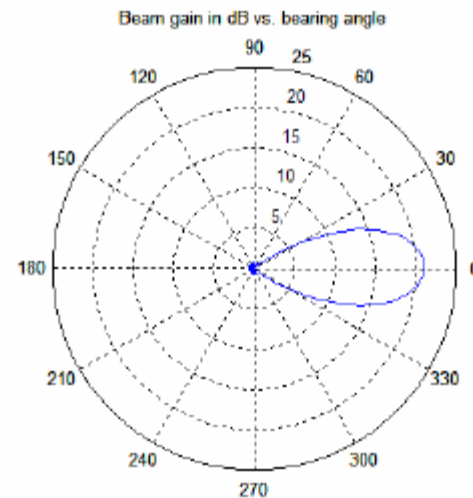


Beamforming is Spatial Filtering

- Sensors in any wave propagation medium (acoustic, electromagnetic) can form a response pattern with higher sensitivity in desired directions.

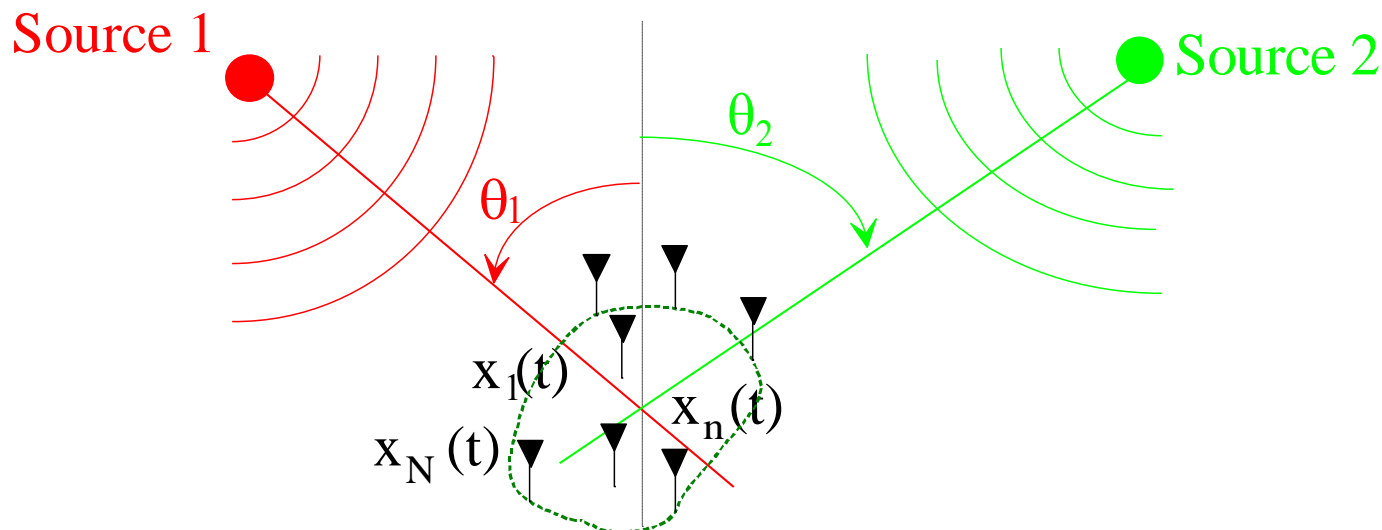


Pencil beam response,
no windowing



Pencil beam response,
Hamming window

LE TRAITEMENT D'ANTENNE

**Estimation :**

- Localisation
- Détection
- Séparation
- Identification

$$\begin{aligned}\mathbf{x}(t) &= \sum_{m=1}^M \mathbf{a}(\theta_m) s_m(t) + \mathbf{b}(t) \\ &= A(\boldsymbol{\theta}) \mathbf{s}(t) + \mathbf{b}(t)\end{aligned}$$

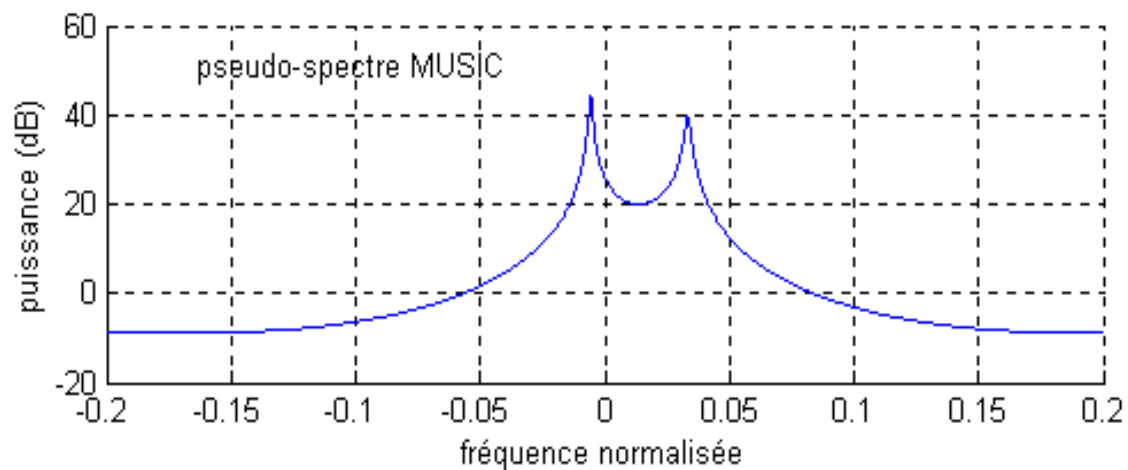
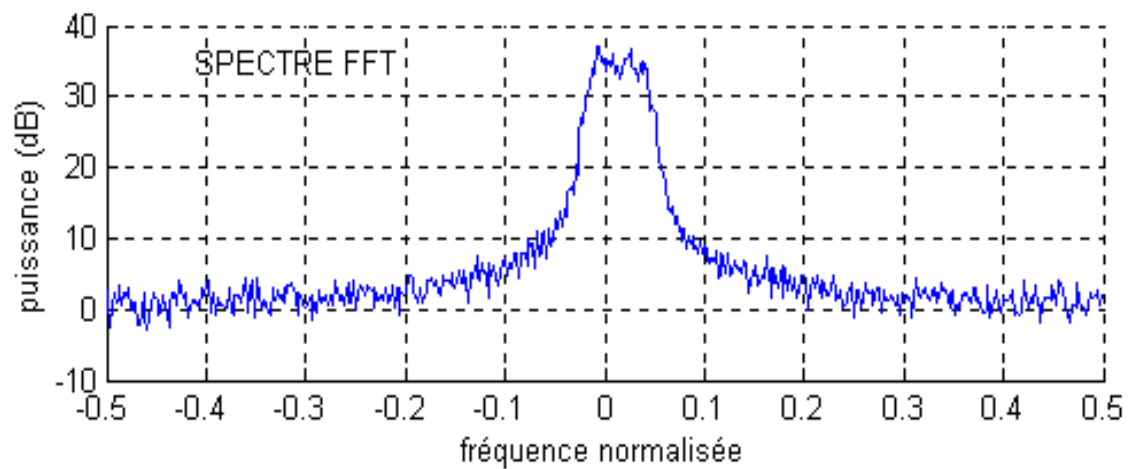
Les méthodes de sous espace : la méthode MUSIC

$$\mathbf{x}(t) = \mathbf{y}(t) + \mathbf{b}(t) = \sum_{m=1}^M \mathbf{a}(\theta_m) s_m(t) + \mathbf{b}(t), \quad \mathbf{x}(t) \in \mathbb{C}^N \quad \text{et} \quad \mathbf{y}(t) \in \mathbb{C}^M \quad N > M$$

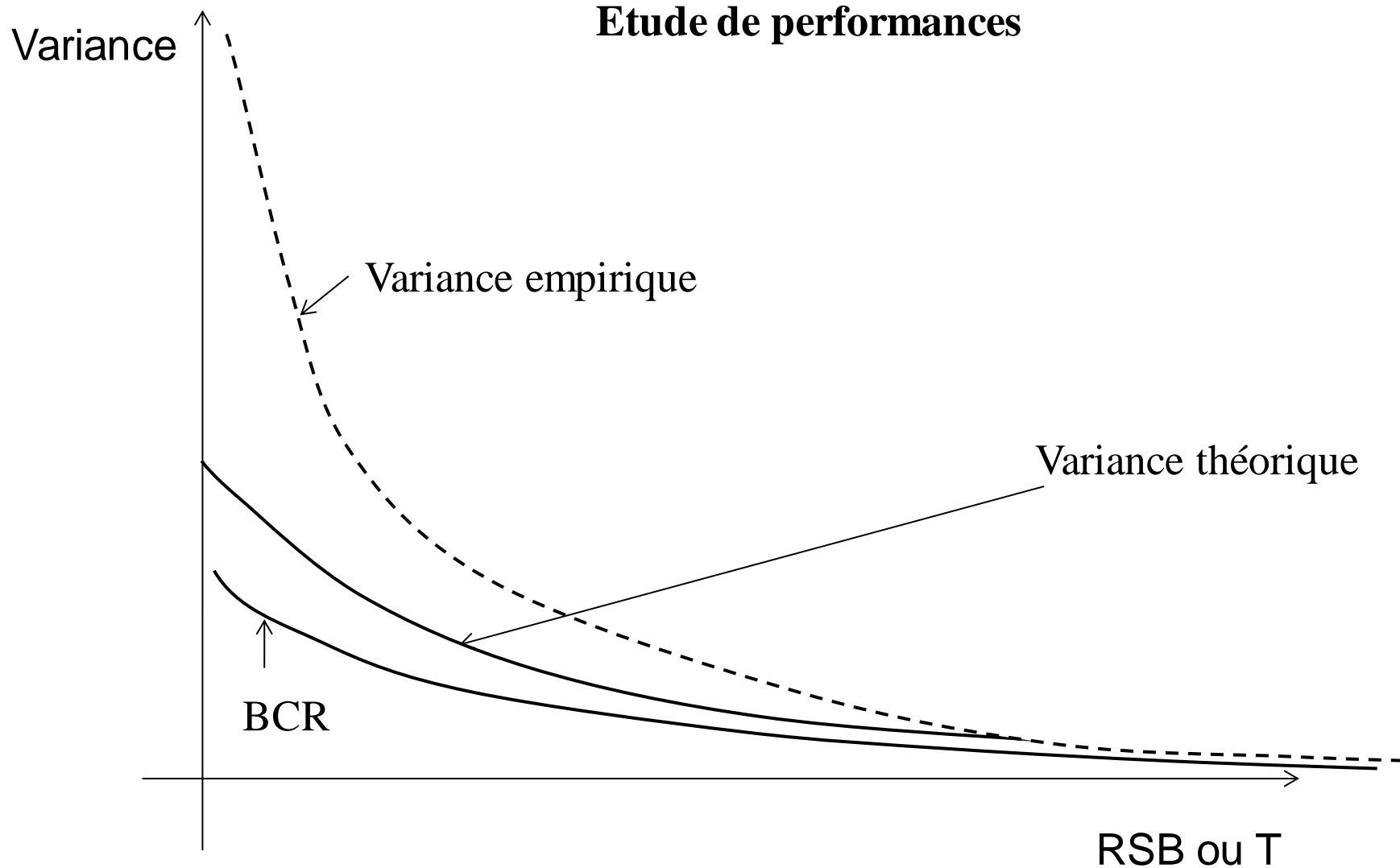
$$\hat{R}_x = \sum_{t=1}^T \mathbf{x}(t) \mathbf{x}(t)^H = \hat{\mathbf{E}}_S \hat{\Lambda}_S \mathbf{E}_S^H + \hat{\mathbf{E}}_B \hat{\Lambda}_B \hat{\mathbf{E}}_B^H$$

$$R_x = E \left[\mathbf{x}(t) \mathbf{x}(t)^H \right] = E \left[\hat{R}_x \right] = \mathbf{E}_S \Lambda_S \mathbf{E}_S^H + \mathbf{E}_B \Lambda_B \mathbf{E}_B^H$$

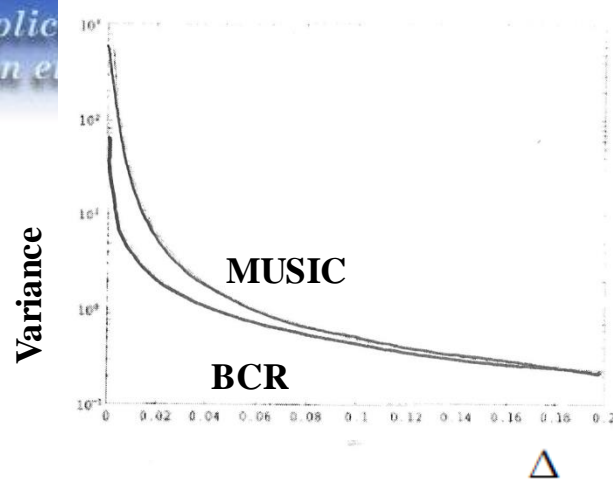
$$\begin{array}{l} \text{Vect}(\mathbf{E}_S) = \text{Vect}(\mathbf{A}) \\ \text{Vect}(\mathbf{E}_B) \perp \text{Vect}(\mathbf{A}) \end{array} \quad \longrightarrow \quad \hat{\theta} = \arg \min_{\theta} \frac{1}{\mathbf{a}(\theta)^H \hat{\mathbf{E}}_B \hat{\mathbf{E}}_B^H \mathbf{a}(\theta)} = \arg \min_{\theta} \frac{1}{\mathbf{a}(\theta)^H \Pi_B \mathbf{a}(\theta)}$$



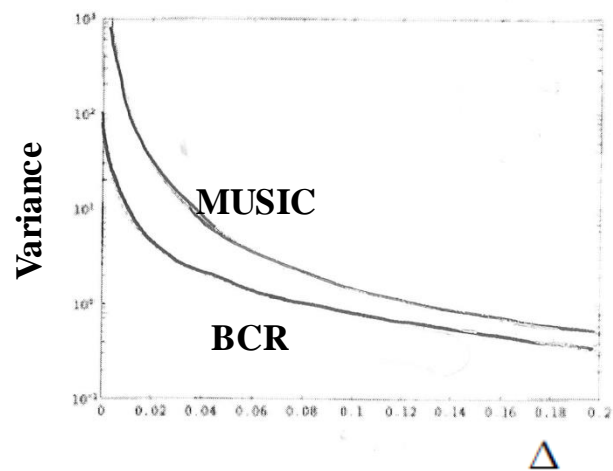
Etude de performances



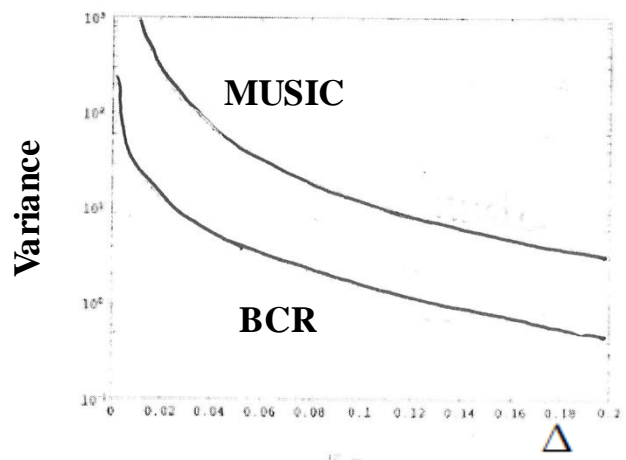
BCR : Borne Cramer Rao



$$\rho = 0.5$$

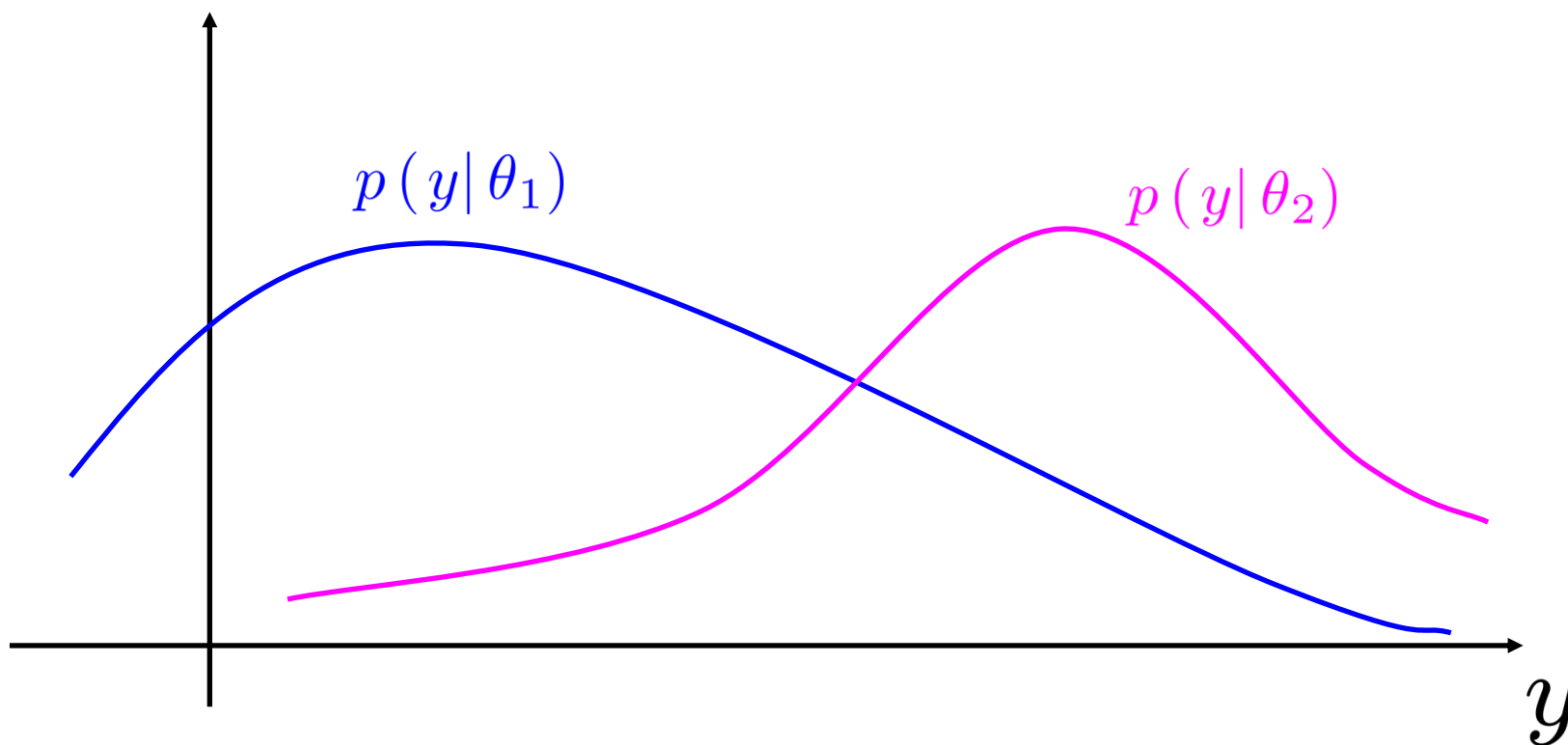


$$\rho = 0.9$$

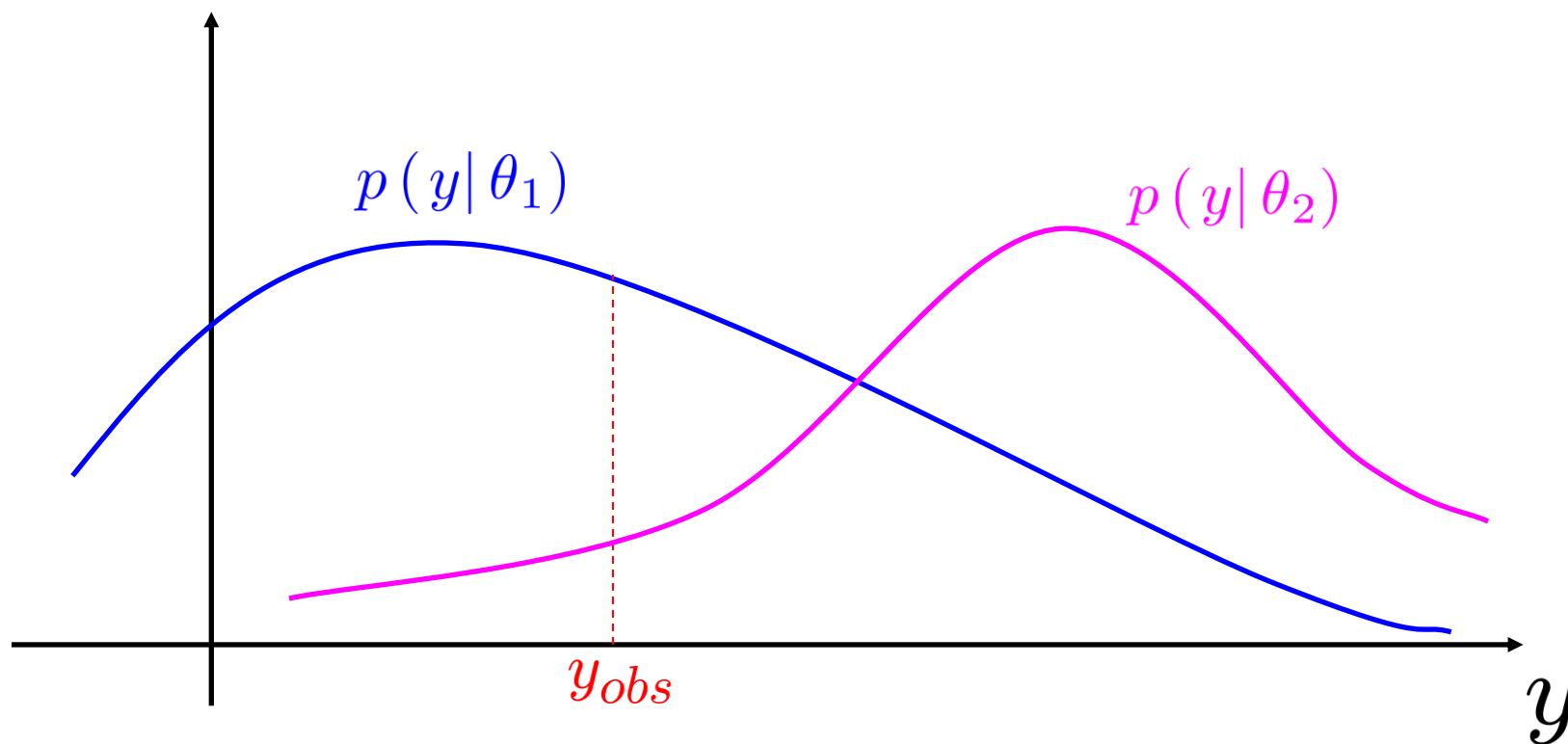


$$\rho = 0.99$$

Maximum de vraisemblance : principe

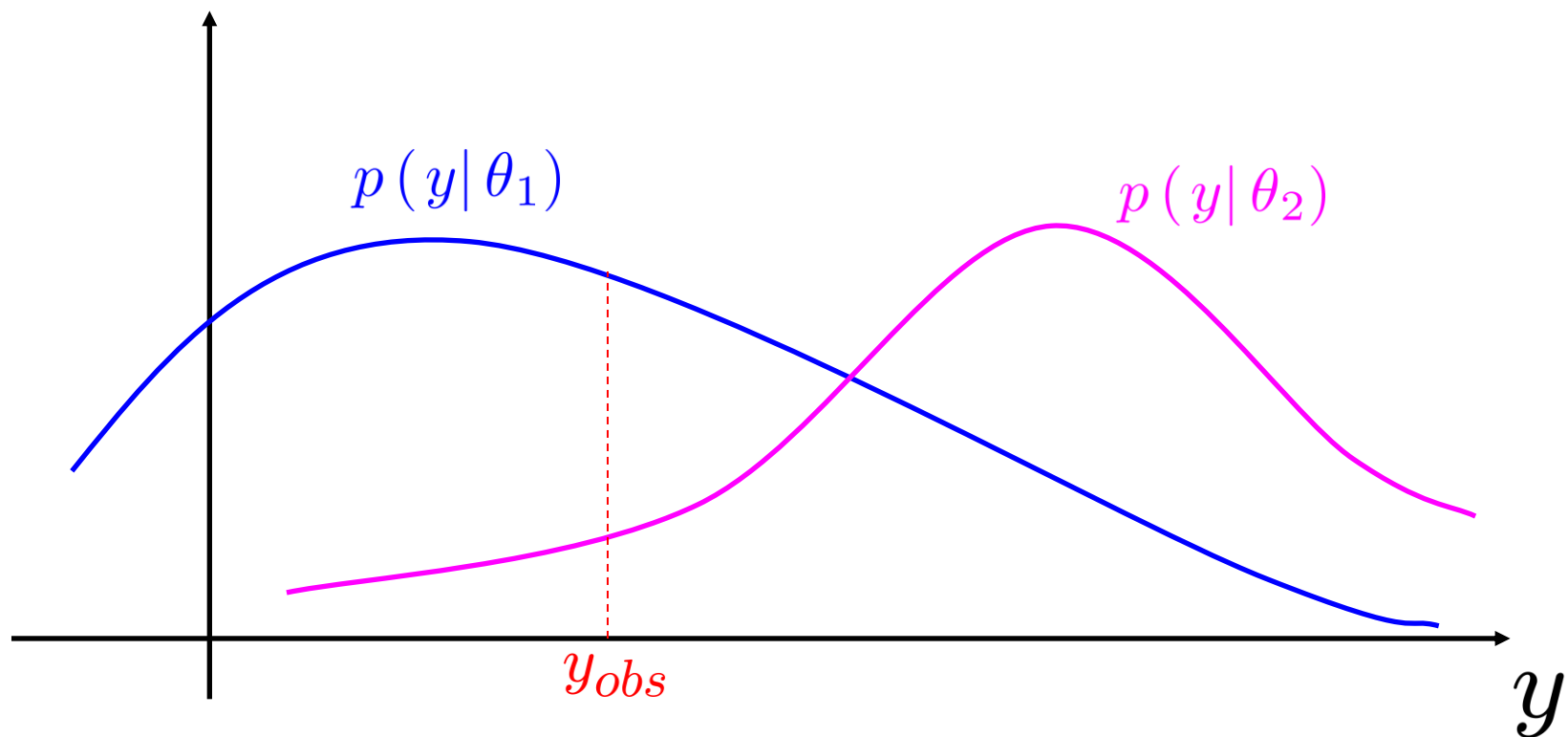


Maximum de vraisemblance : principe



$$\hat{\theta}_{ML}(y_{obs}) = \theta_1$$

Maximum de vraisemblance : principe



Généralisation $\hat{\theta}_{ML}(y_{obs}) = \arg \max_{\theta} p(y_{obs} | \theta)$

Maximum de vraisemblance en traitement d'antenne

$$\mathbf{y}(t) = \mathbf{A}(\boldsymbol{\theta}) \mathbf{s}(t) + \mathbf{b}(t) \quad t = 1 \dots N$$

Hypothèses

$$\mathbf{s}(t) \sim \mathcal{N}_{\mathbb{C}}(\mathbf{0}, \boldsymbol{\Sigma}_s)$$

aléatoires

Paramètres à estimer

$$\boldsymbol{\theta}, \sigma^2, \boldsymbol{\Sigma}_s$$

Maximum de Vraisemblance
stochastique

$$\mathbf{s}(t) \quad t = 1 \dots N$$

déterministes

Paramètres à estimer

$$\boldsymbol{\theta}, \sigma^2, \mathbf{s}_1, \dots, \mathbf{s}_N$$

Maximum de Vraisemblance
déterministe

Maximum de Vraisemblance stochastique

$$\mathbf{y}(t) = \mathbf{A}(\boldsymbol{\theta}) \mathbf{s}(t) + \mathbf{b}(t) \quad \mathbf{s}(t) \sim \mathcal{N}_{\mathbb{C}}(\mathbf{0}, \boldsymbol{\Sigma}_s)$$

$$\mathbf{y}(t) \sim \mathcal{N}_{\mathbb{C}}(\mathbf{0}, \boldsymbol{\Sigma}_y)$$

$$\boldsymbol{\Sigma}_y = \mathbf{A}(\boldsymbol{\theta}) \boldsymbol{\Sigma}_s \mathbf{A}^H(\boldsymbol{\theta}) + \sigma^2 \mathbf{I}$$

$$\begin{cases} \hat{\boldsymbol{\theta}}_{MVS} = \arg \min_{\boldsymbol{\theta}} \left| \mathbf{A}(\boldsymbol{\theta}) \hat{\mathbf{R}}_s \mathbf{A}^H(\boldsymbol{\theta}) + \hat{\sigma}^2 \mathbf{I} \right| \\ \hat{\sigma}^2 = \frac{1}{M-K} \text{Trace} \left\{ \boldsymbol{\Pi}_{\mathbf{A}}^{\perp}(\boldsymbol{\theta}) \hat{\boldsymbol{\Sigma}}_y \right\} \\ \hat{\mathbf{R}}_s = \mathbf{A}^{\dagger} \left(\hat{\boldsymbol{\Sigma}}_y - \hat{\sigma}^2 \mathbf{I} \right) \mathbf{A}^{\dagger H} \end{cases}$$

Borne de Cramér-Rao Stochastique

$$\mathbf{BCRS}(\boldsymbol{\theta}_0) = \frac{\sigma^2}{2N} \left[\text{Re} \left\{ \mathbf{H}(\boldsymbol{\theta}_0) \odot \boldsymbol{\Sigma}_s \mathbf{A}^H(\boldsymbol{\theta}_0) \boldsymbol{\Sigma}_y^{-1} \mathbf{A}(\boldsymbol{\theta}_0) \boldsymbol{\Sigma}_s \right\} \right]^{-1}$$

Maximum de Vraisemblance déterministe

$$\mathbf{y}(t) = \mathbf{A}(\boldsymbol{\theta}) \mathbf{s}(t) + \mathbf{b}(t) \quad \mathbf{s}(t) \quad t = 1 \dots N$$

déterministes

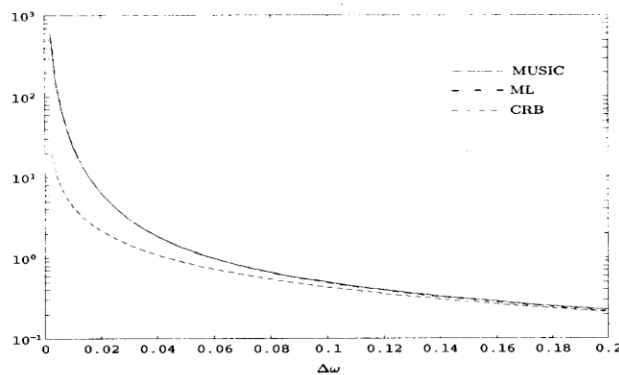
$$\mathbf{y}(t) \sim \mathcal{N}_{\mathbb{C}}(\mathbf{A}(\boldsymbol{\theta}) \mathbf{s}(t), \boldsymbol{\Sigma}_y)$$

$$\boldsymbol{\Sigma}_y = \sigma^2 \mathbf{I}$$

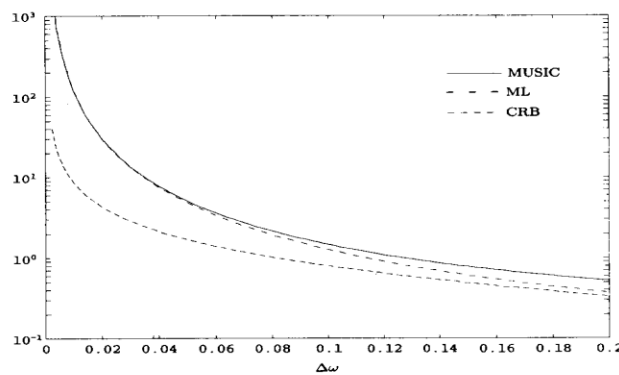
$$\begin{cases} \hat{\boldsymbol{\theta}}_{MVD} = \arg \min_{\boldsymbol{\theta}} \text{Trace} \left\{ \boldsymbol{\Pi}_{\mathbf{A}}^{\perp}(\boldsymbol{\theta}) \hat{\boldsymbol{\Sigma}}_y \right\} \\ \hat{\boldsymbol{\Sigma}}_y = \frac{1}{N} \sum_{t=1}^N \mathbf{y}(t) \mathbf{y}^H(t) \end{cases}$$

Borne de Cramér-Rao Déterministe

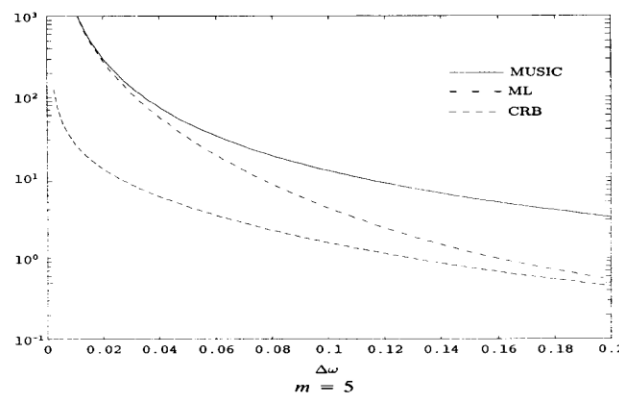
$$\text{BCRD}(\boldsymbol{\theta}_0) = \frac{\sigma^2}{2N} \left[\text{Re} \left\{ \mathbf{H}(\boldsymbol{\theta}_0) \odot \hat{\boldsymbol{\Sigma}}_s \right\} \right]^{-1}$$



$\rho = 0.5$



$\rho = 0.9$

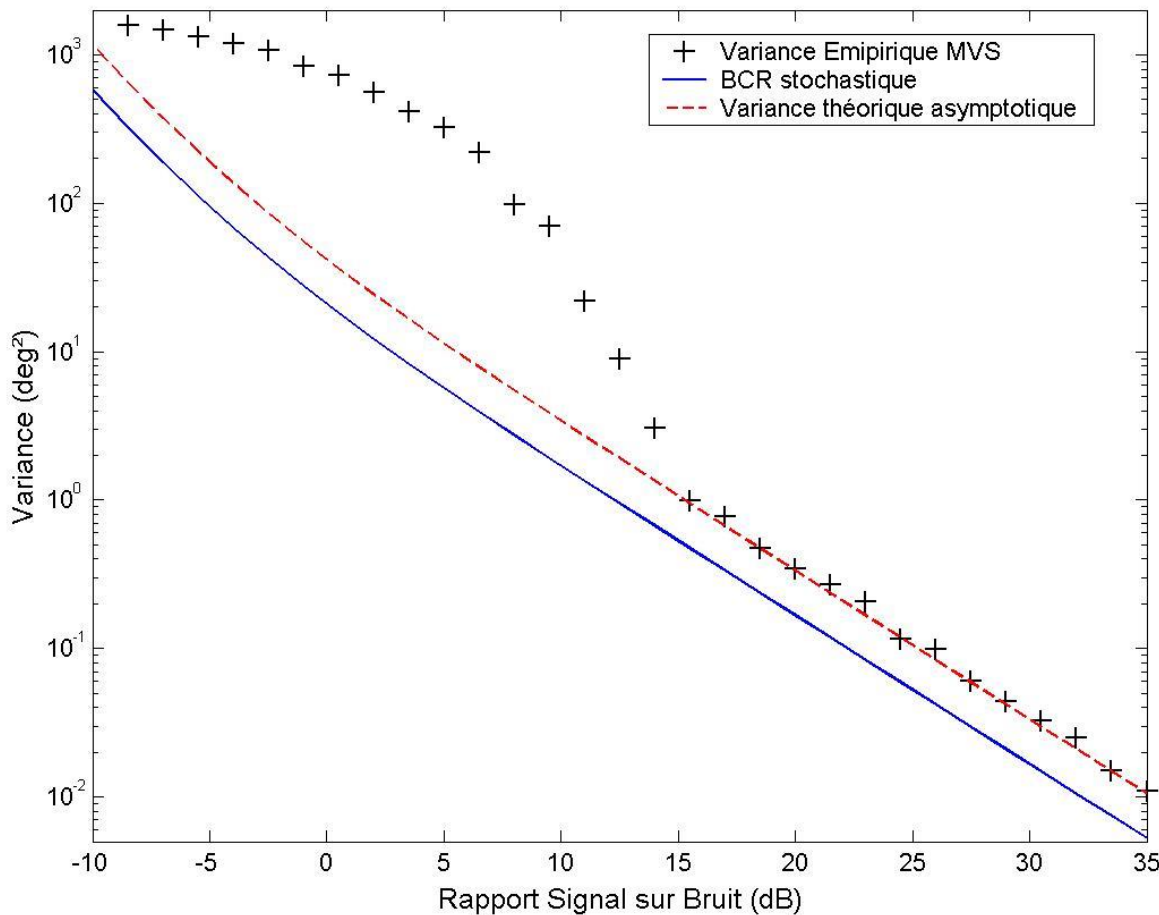


$\rho = 0.99$

$m = 5$

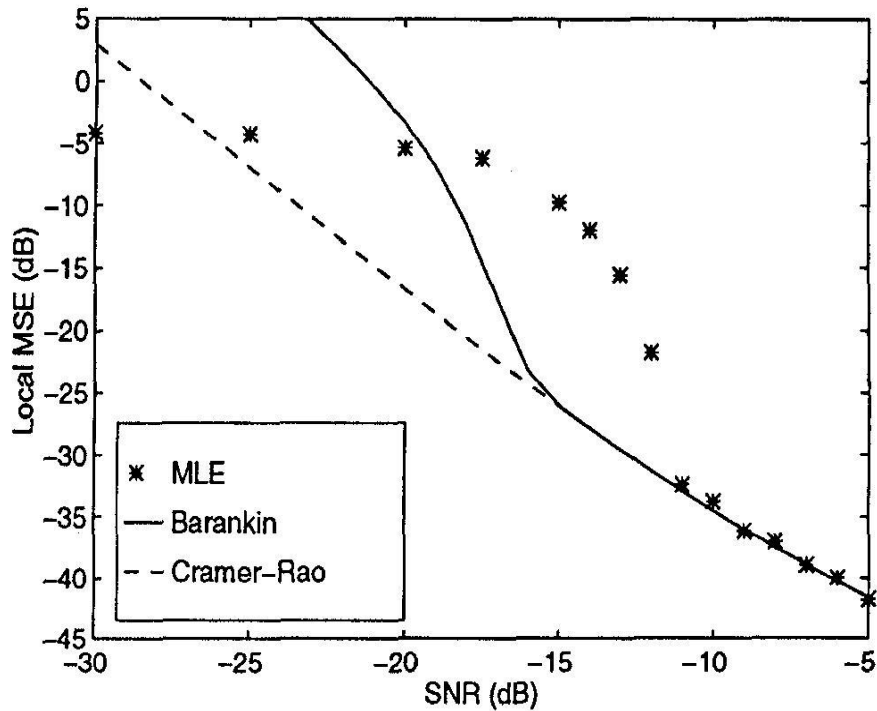
Performances asymptotiques

Cas particulier : scénario une source

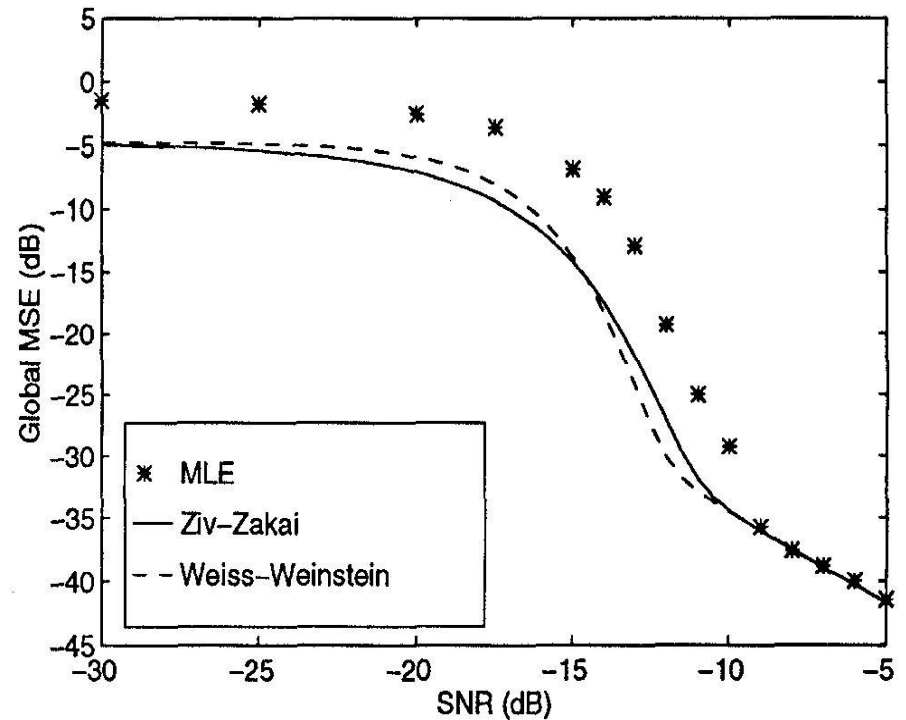


- ALU ($\lambda/2$) : $M = 4$ capteurs
- $N = 2$ observations
- 1 source 0°
- 1000 Monte Carlos

BORNES MINIMALES



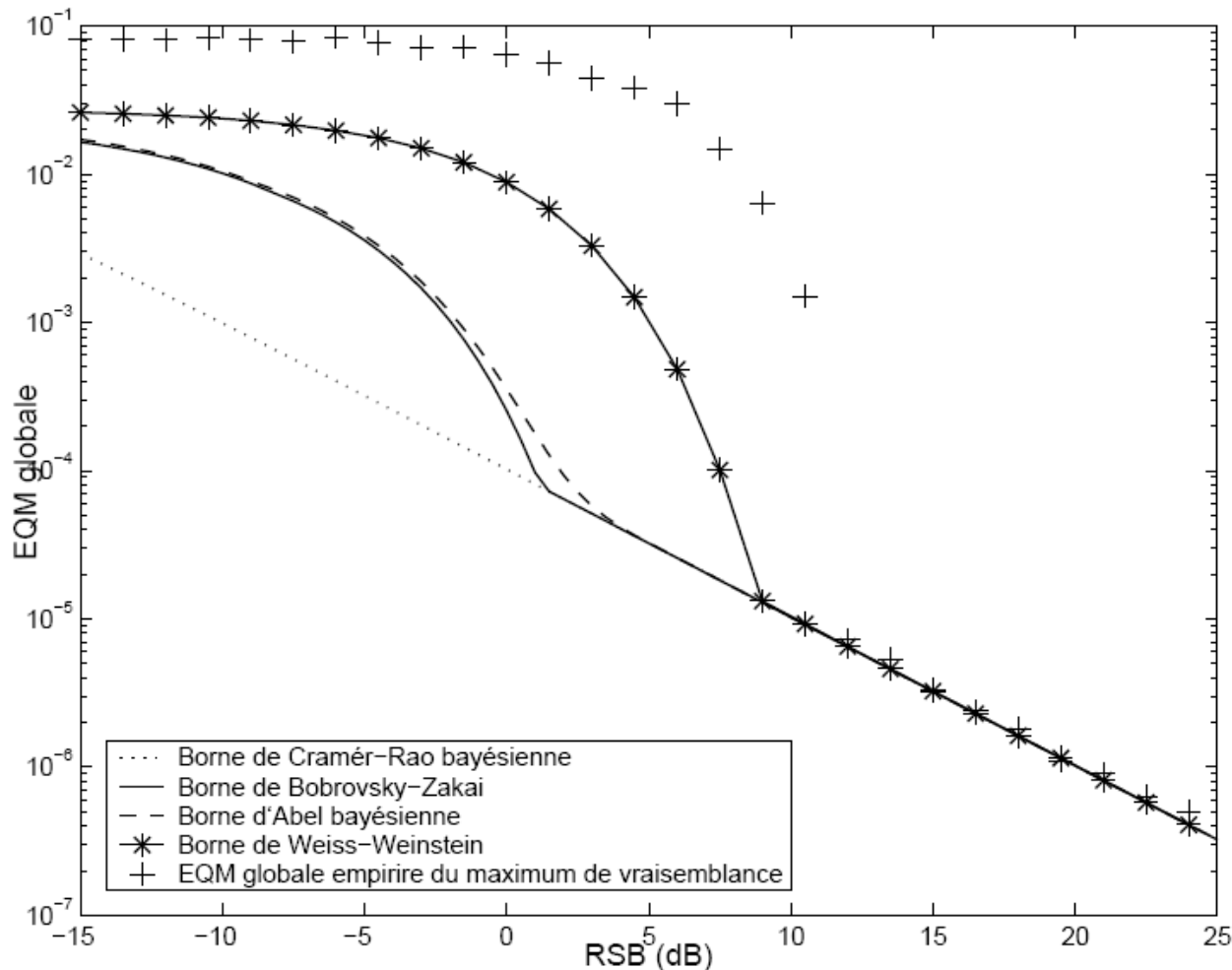
Paramètres Déterministes



Paramètres aléatoires

Bornes minimales en traitement du signal

Application à la synchronisation (analyse spectrale)

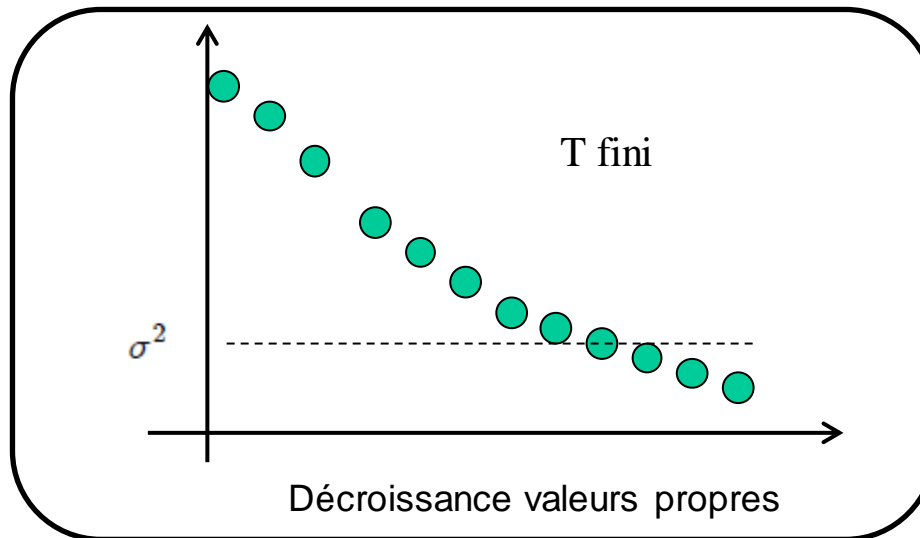
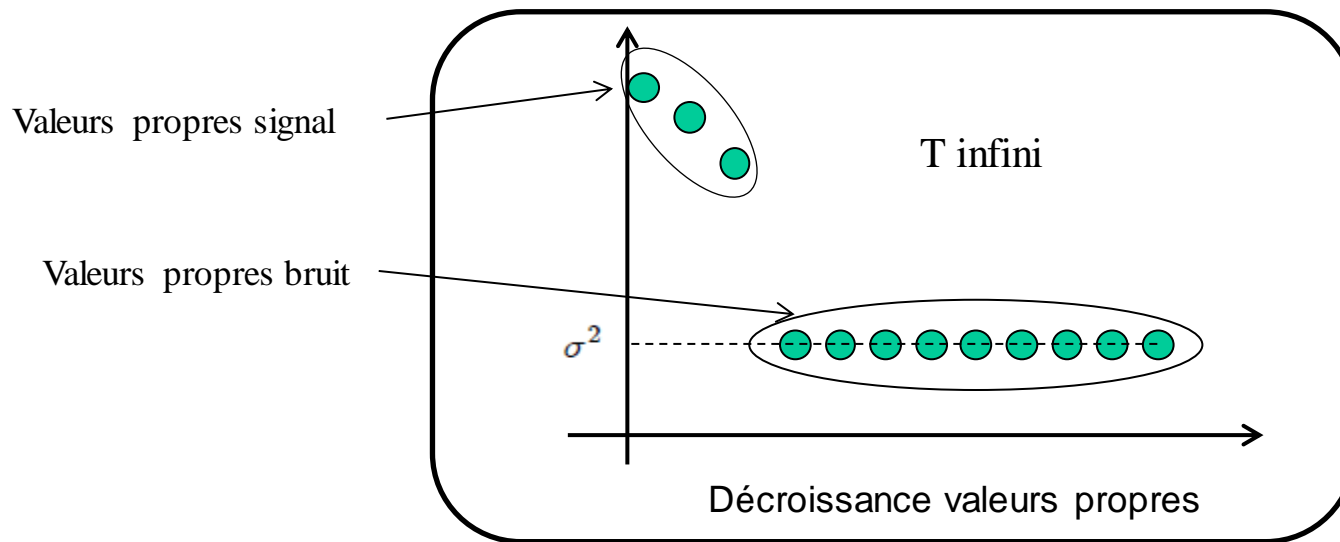


20 observations

Maximum de
Vraisemblance

EQM Globale

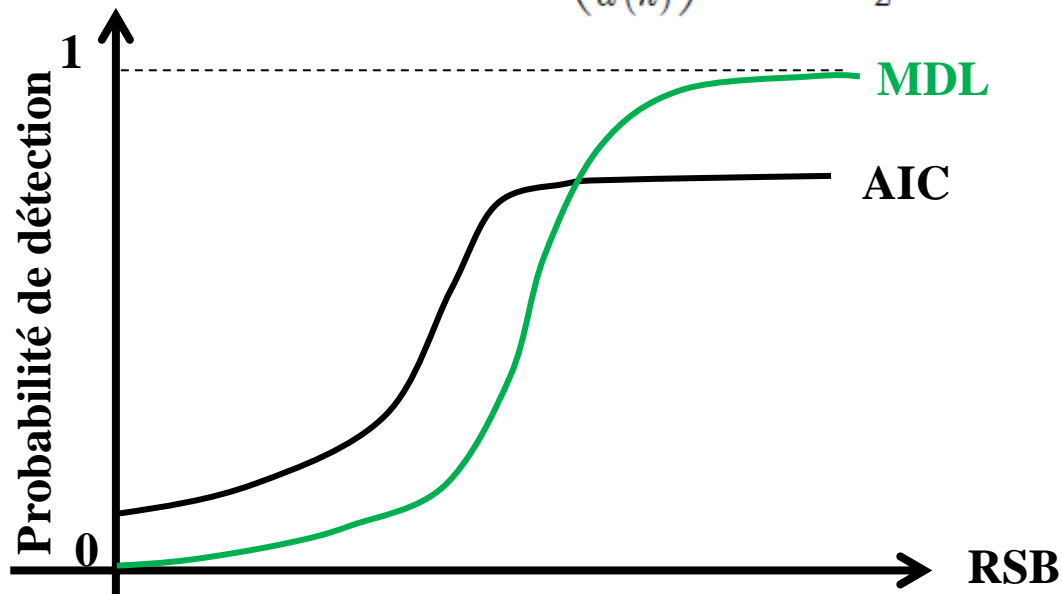
Sélection de l'ordre



Sélection fondée sur la théorie de l'information

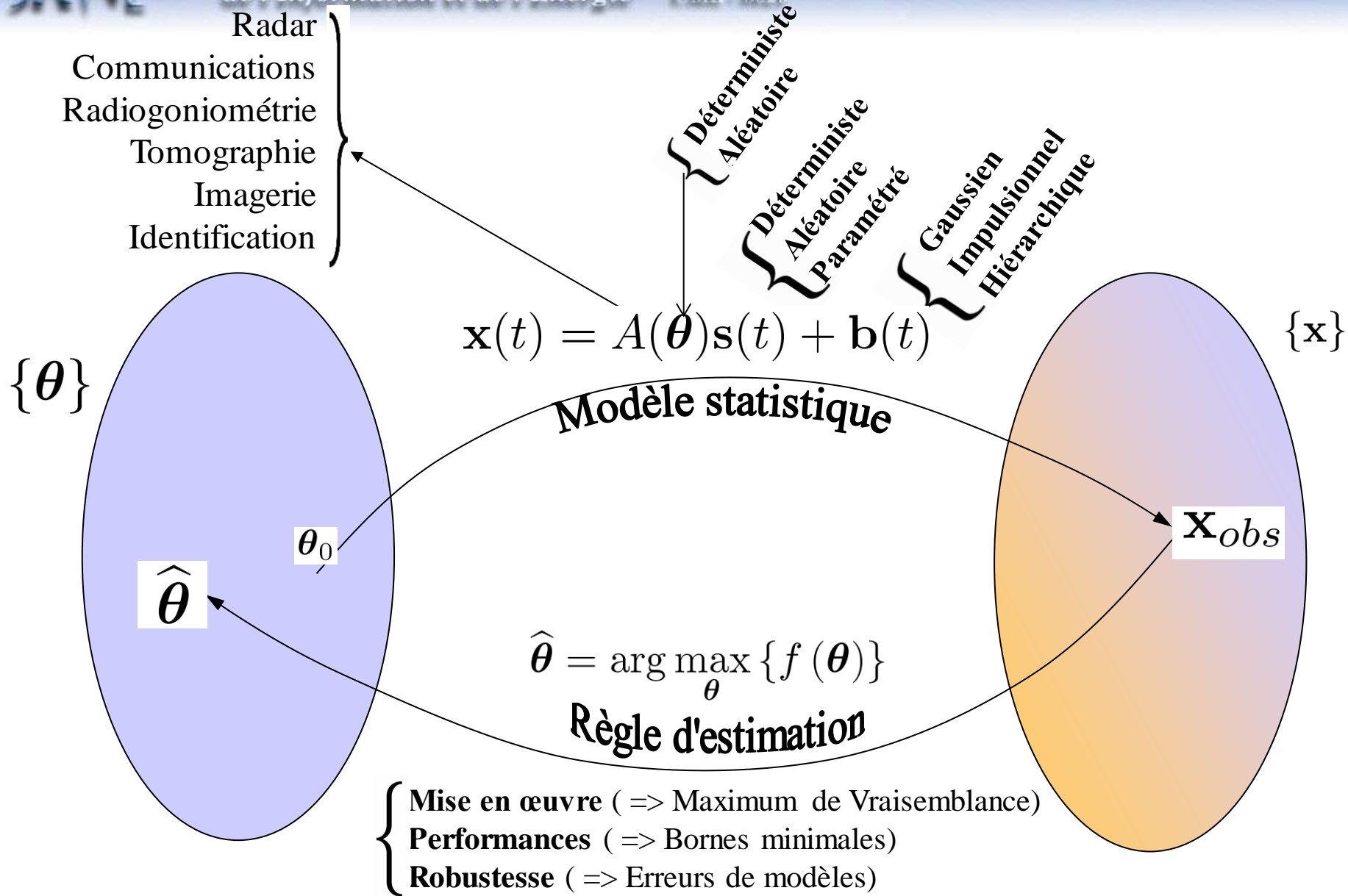
Akaike(74) $AIC(k) = -LV(k) + NPL = -\log \left(\frac{g(k)}{a(k)} \right)^{T(N-k)} + k(2N - k)$

Rissanen et Schwartz(78) $MDL(k) = -\log \left(\frac{g(k)}{a(k)} \right)^{T(N-k)} + \frac{1}{2}k(2N - k) \log(T)$



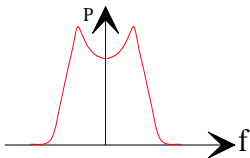
Réglage de la probabilité de fausse alarme \longrightarrow Théorie de la décision

Rapport de vraisemblance $RV(k) = \left(\frac{a(k)}{g(k)} \right)^{T(N-k)} \leq s(k)$

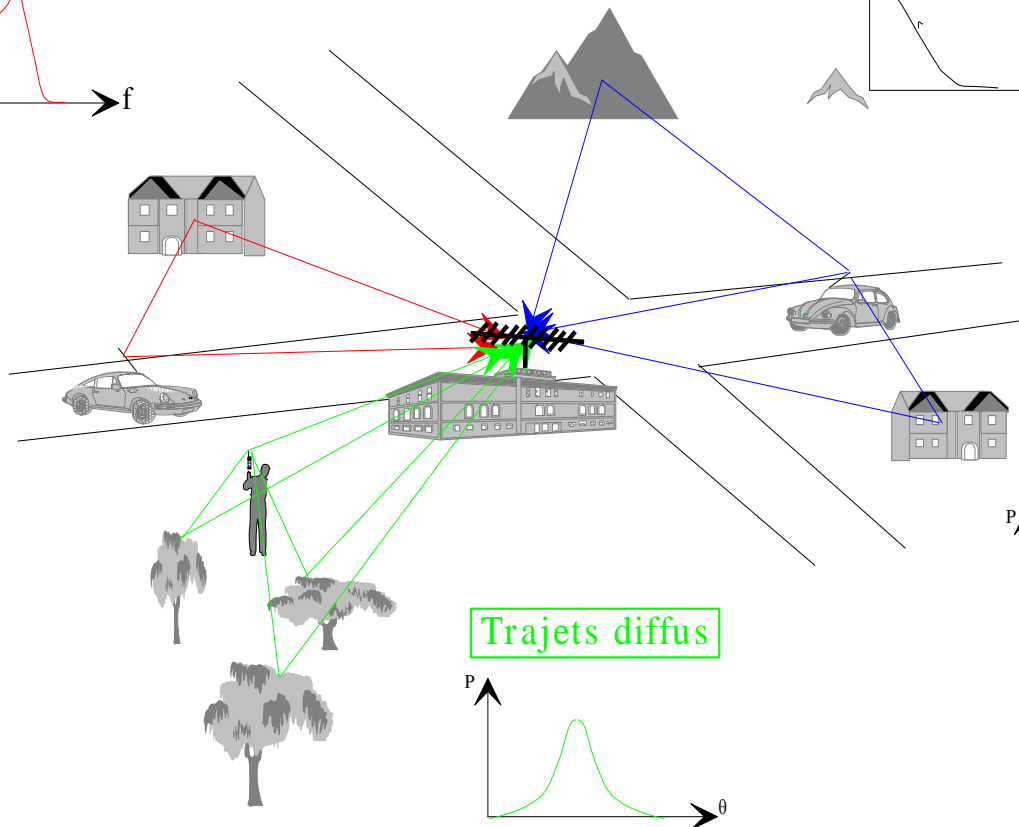
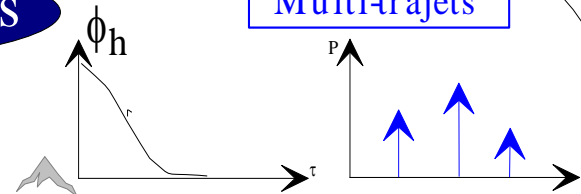


Communications mobiles

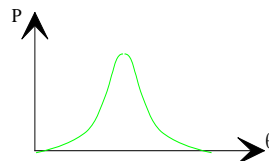
Effet Doppler



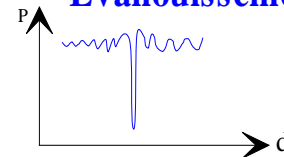
Multi-trajets



Trajets diffus



Evanouissement



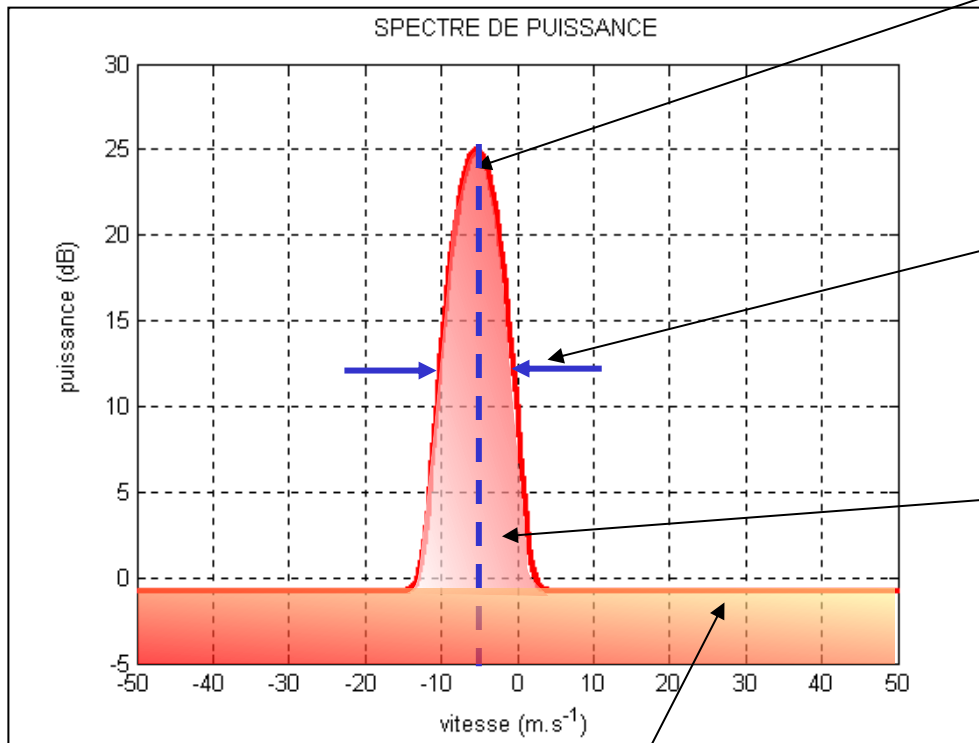
$$h(\tau, t_0) = \sum_{m=1}^M \alpha_m(t_0) \delta(\tau - \tau_m(t_0))$$

Estimation d'échos Doppler par radars strato-troposphériques Le cyclone Georges





Paramètres d'intérêt



Vent moyen (Doppler)

Renseigne sur la valeur et le sens du vent radial

Ecart-type de l'écho

Mesure la dispersion des vitesses par rapport à la vitesse moyenne

Puissance de l'écho

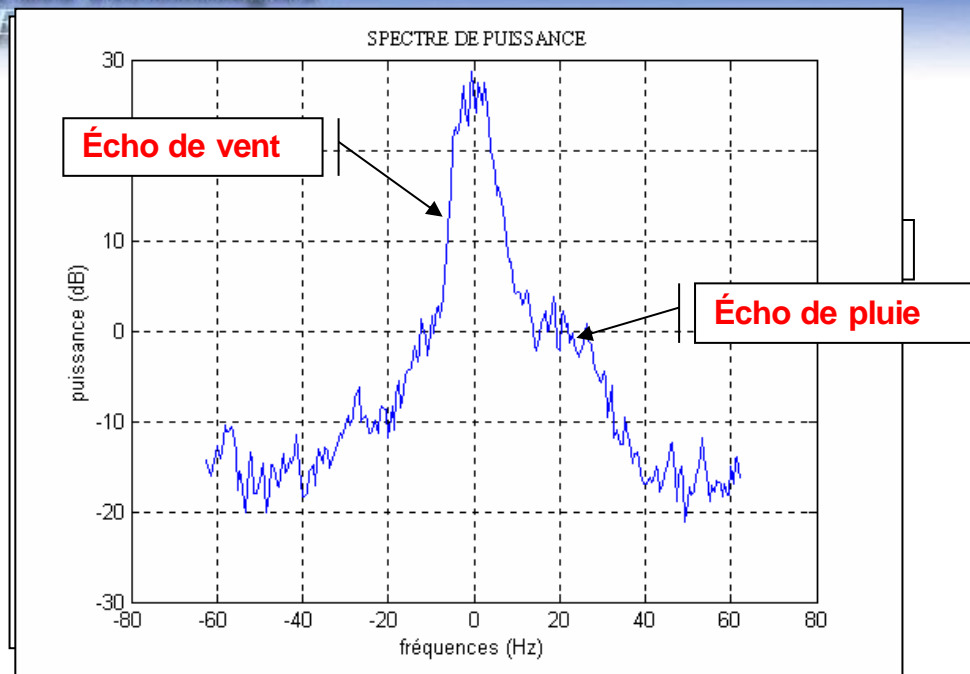
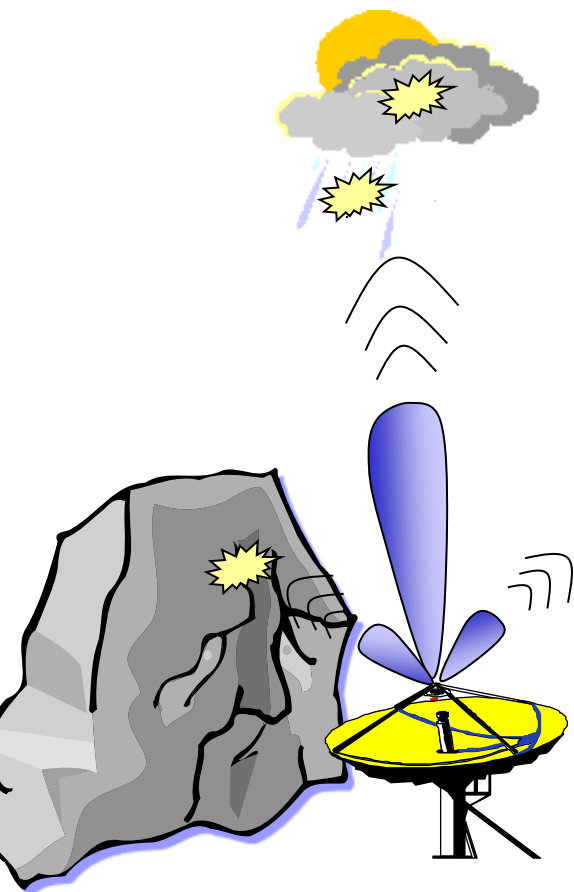
Donne une estimation de la réflectivité qui est liée à l'intensité de la turbulence

Puissance de bruit

Paramètre de nuisance

$$P_0 \ ; \ v_0 = -\frac{\lambda}{2} f_0 \ ; \ \sigma_0$$

3 paramètres d'intérêt à estimer



En cas d'échos multiples fortement superposés, peut-on estimer correctement les paramètres d'intérêt ?

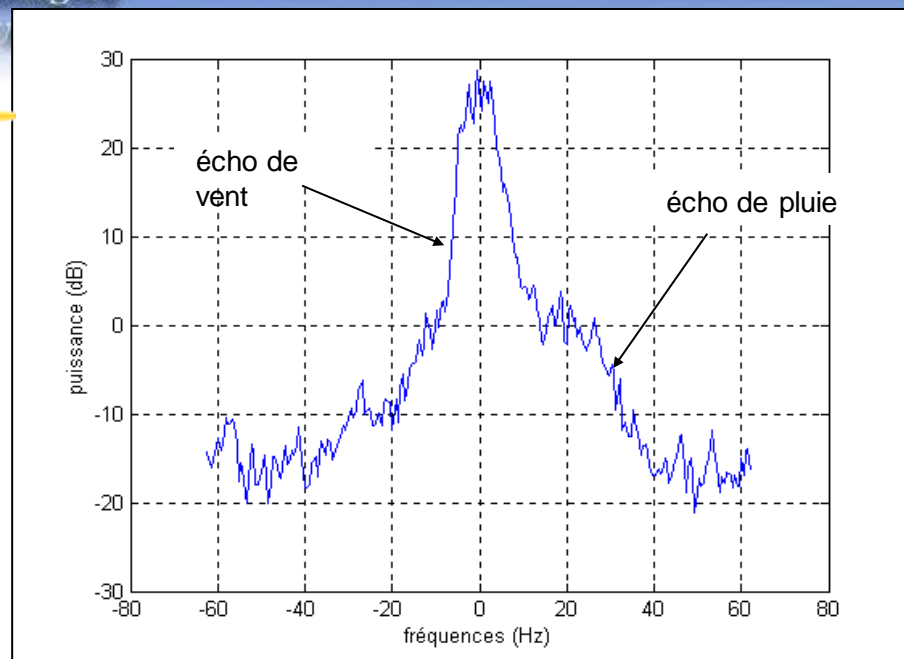
Modèle paramétrique des échos radar

HYP : LES ECHOS SONT GAUSSIENS

Spectre de puissance

$$P_s(f) = \sum_{i=1}^N S_i(f) + \sigma_b^2,$$

$$S_i(f) = \frac{P_i}{\sqrt{2\pi} \cdot \sigma_i} e^{-\frac{1}{2} \left(\frac{f-f_i}{\sigma_i} \right)^2}$$



$$\mathbf{x} = \mathbf{y} + \mathbf{b} \quad \begin{cases} \mathbf{y} \text{ vecteur aléatoire gaussien centré} \\ \mathbf{b} \text{ bruit blanc complexe gaussien indépendant de } \mathbf{y}, \text{ de variance } \sigma_b^2 \end{cases}$$

$$\mathbf{x} \in \mathcal{N}(0, \mathbf{R}_x)$$

$$\mathbf{R}_x(\boldsymbol{\mu}) = E(\mathbf{x}\mathbf{x}^H) = \sum_{i=1}^N \mathbf{R}_{y_i}(P_i, \omega_i, \sigma_i^2) + \sigma_b^2 \mathbf{I}$$

$$\mathbf{R}_{y_i}(P_i, \omega_i, \sigma_i^2) = P_i \cdot \mathbf{A}(\omega_i) \mathbf{B}(\sigma_i^2) \mathbf{A}^H(\omega_i)$$

$$\mathbf{A}(\omega_i) = \text{diag}(1, e^{j\omega_i T_s}, \dots, e^{j(m-1)\omega_i T_s})$$

$$\mathbf{B}_{k,l}(\sigma_i^2) = e^{-2\pi^2 \sigma_i^2 (k-l)^2 T_s^2}$$

Vecteur paramètre

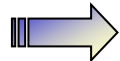
$$\boldsymbol{\mu} = [P_1 \ \omega_1 \ \sigma_1^2 \ \dots \ P_N \ \omega_N \ \sigma_N^2 \ \sigma_b^2]^T$$

Estimation conjointe des moments spectraux

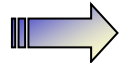


EXPLOITER LA STRUCTURE DE

R_x



Facile à calculer



Porte toute l'information statistique



Elle dépend des paramètres d'intérêt

DEUX APPROCHES RETENUES



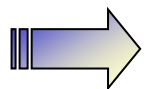
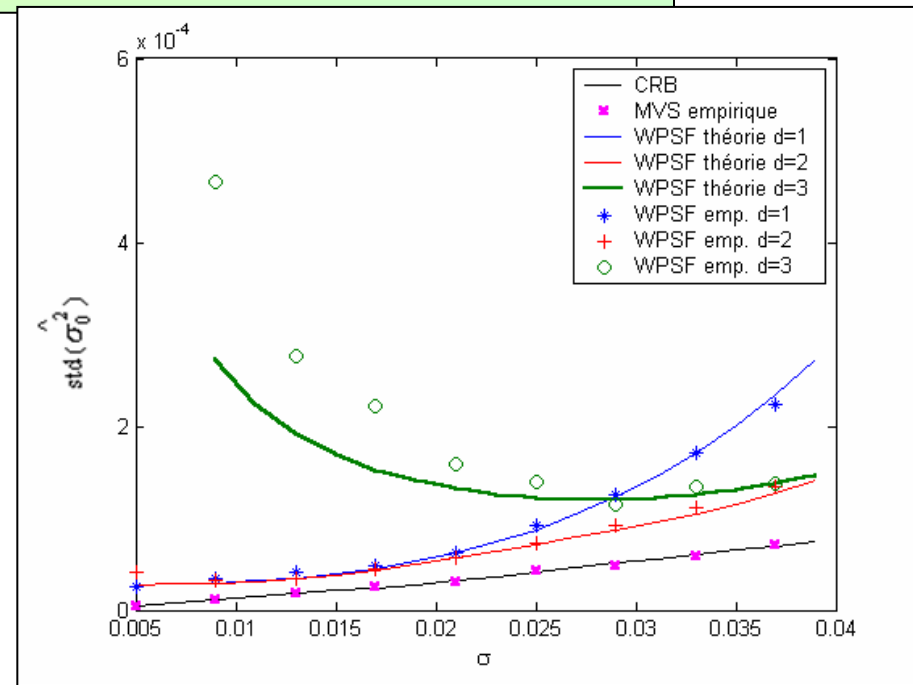
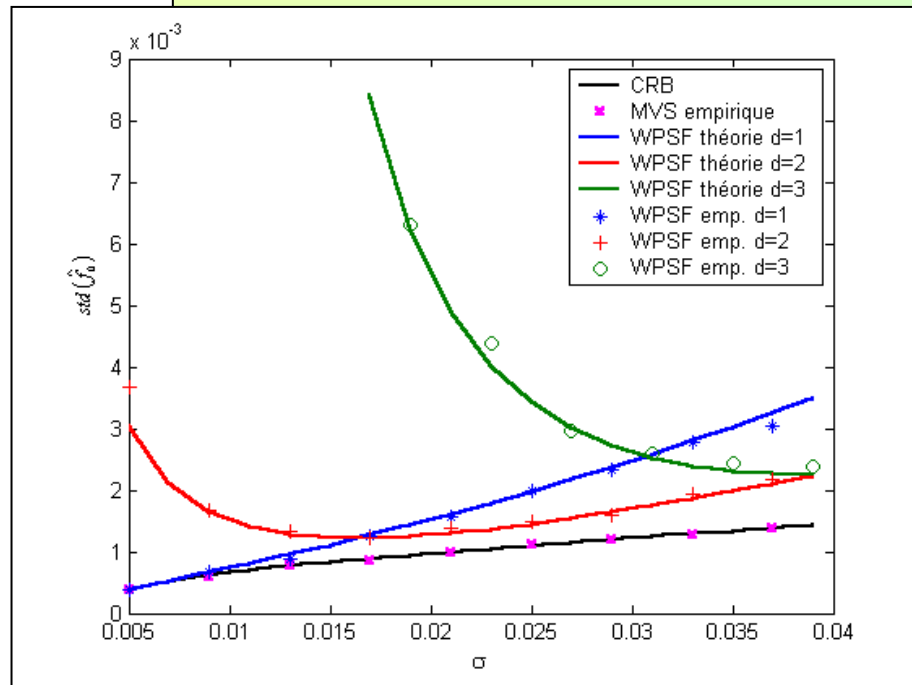
ESTIMATEUR DU MAXIMUM DE VRAISEMBLANCE (MV)



GENERALISATION MULTI-DIMENSIONNELLE DES METHODES DE
SOUS-ESPACE

Simulations – cas de réalisations indépendantes

Performances empiriques et théoriques des estimateurs WPSF et MVS dans le cas d'un écho gaussien



Pour WPSF

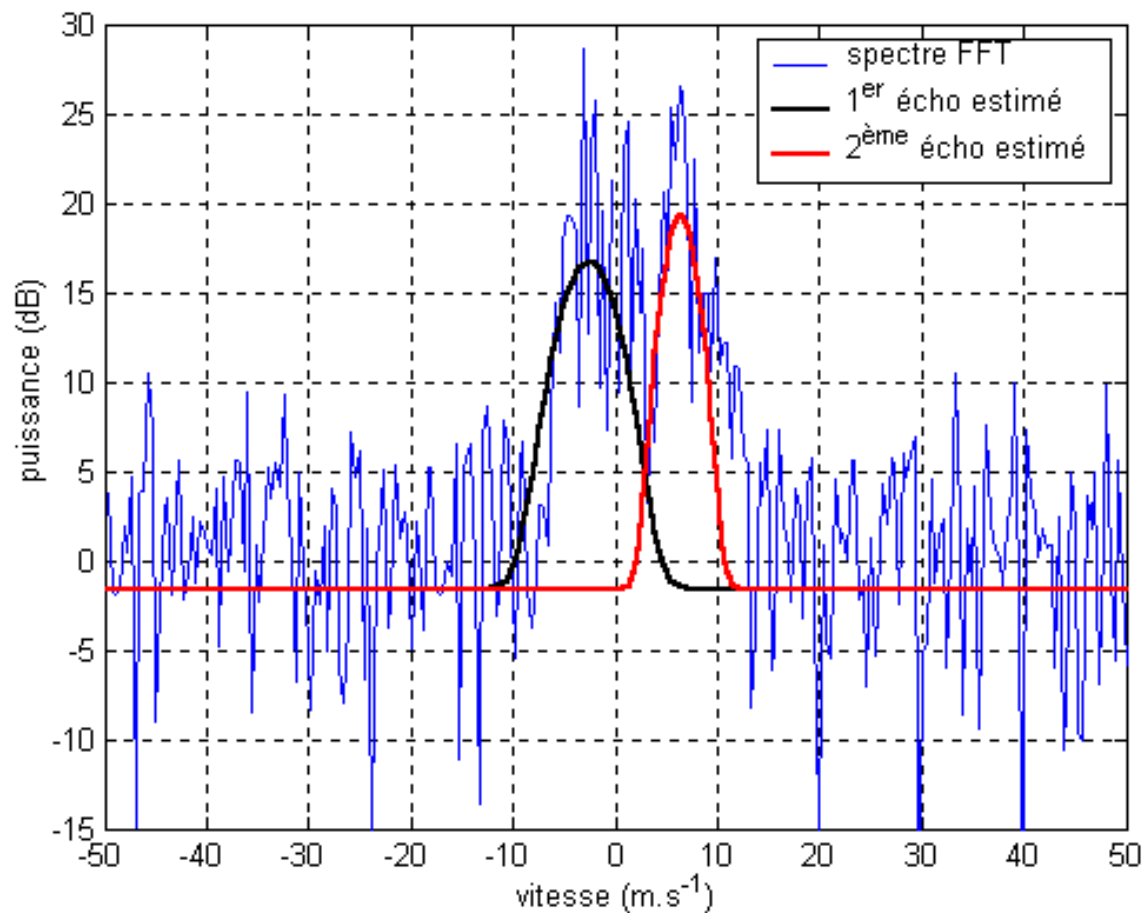


Choix de d crucial



Non optimal

Validation sur données réelles

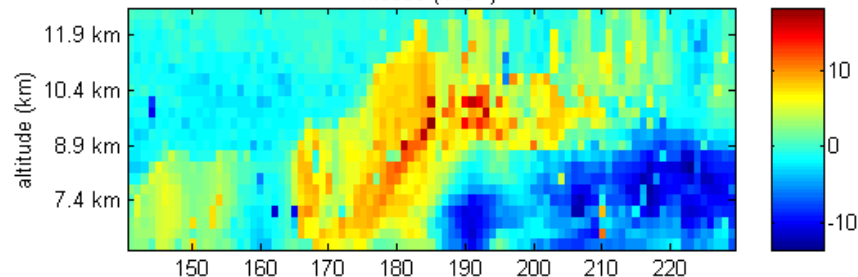


**Estimation MVS d'un signal UHF
avec $M=16384$, $N_{coh}=8$ et $N_{inc}=8$**

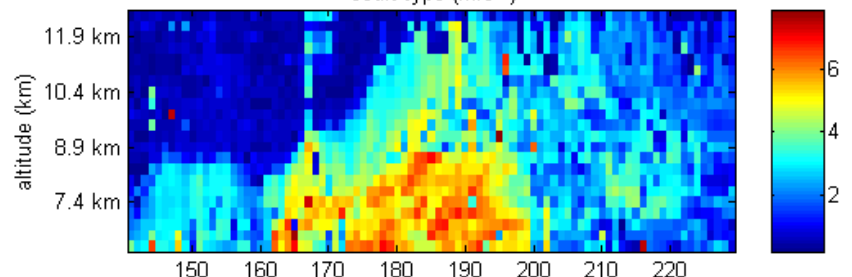
Restitution MVS des échos UHF de vent et de pluie

Echo de vent

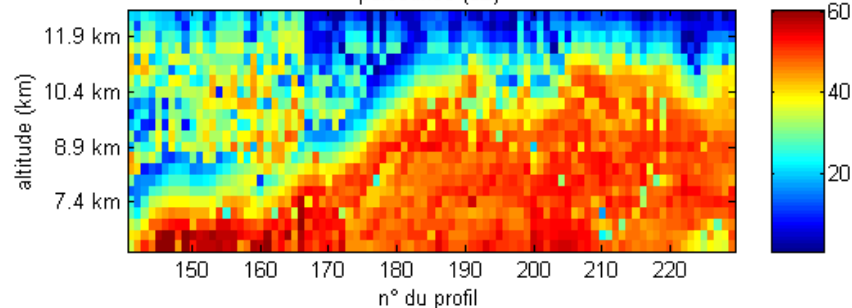
vitesse (m.s^{-1})



écart-type (m.s^{-1})

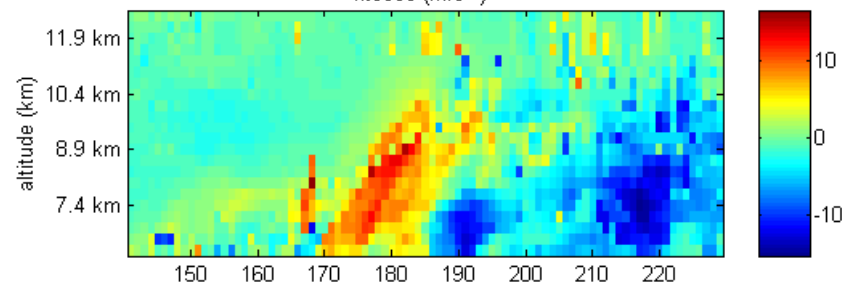


puissance (dB)

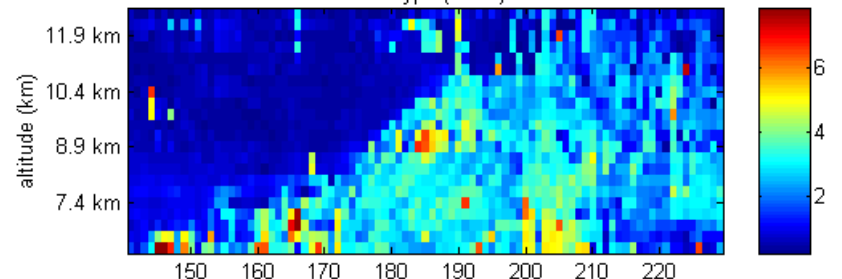


Echo d'hydrométéores

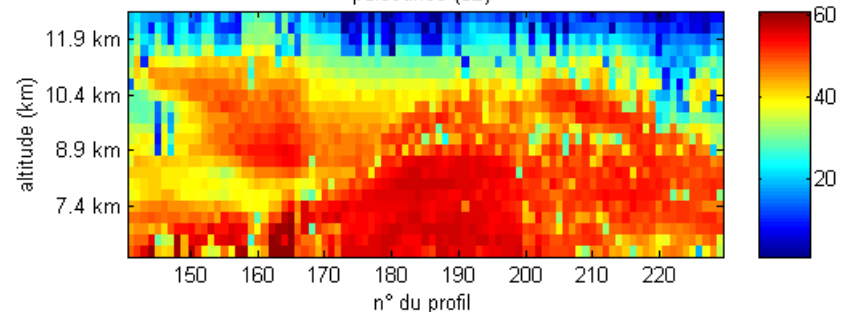
vitesse (m.s^{-1})



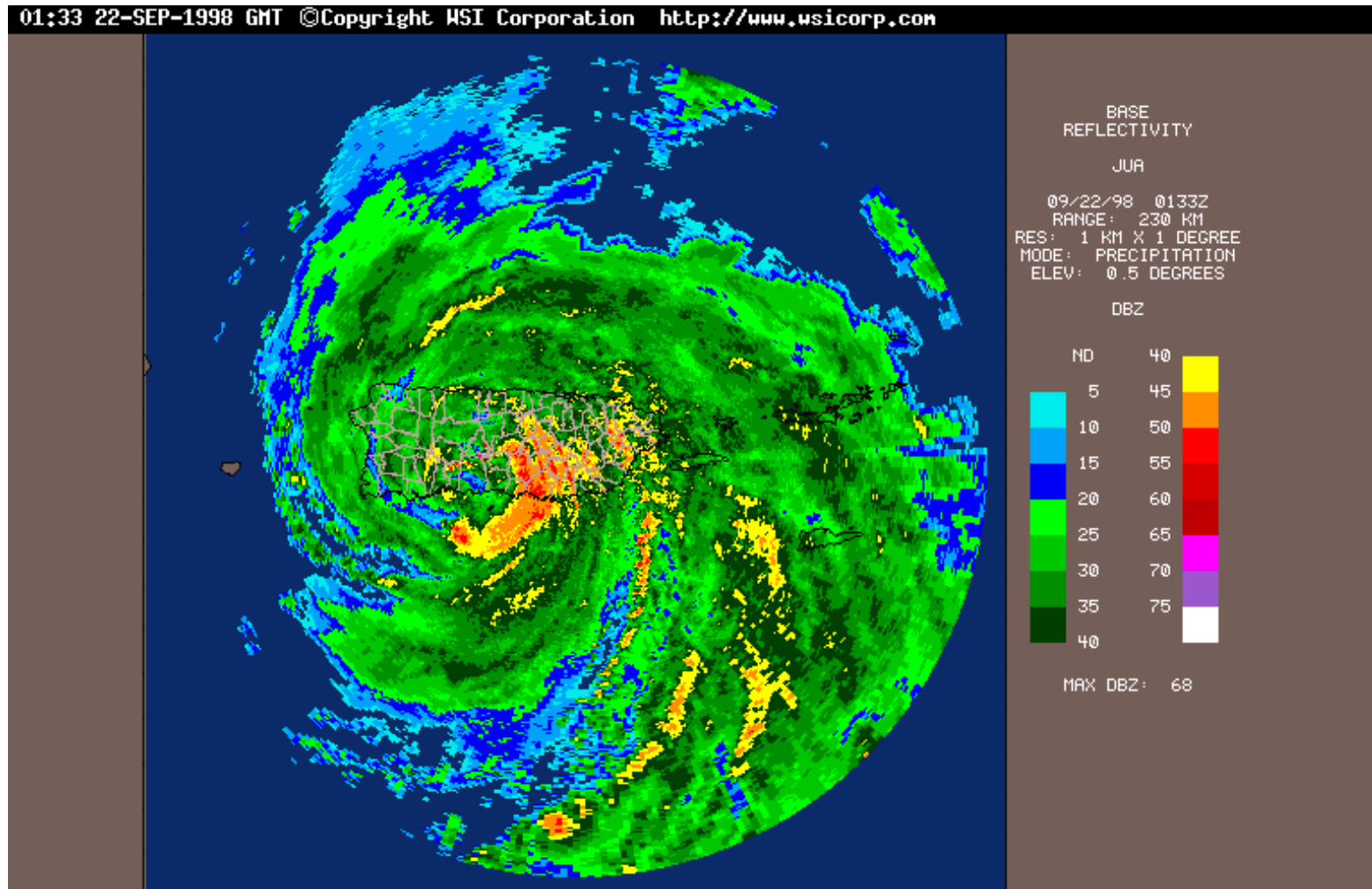
écart-type (m.s^{-1})

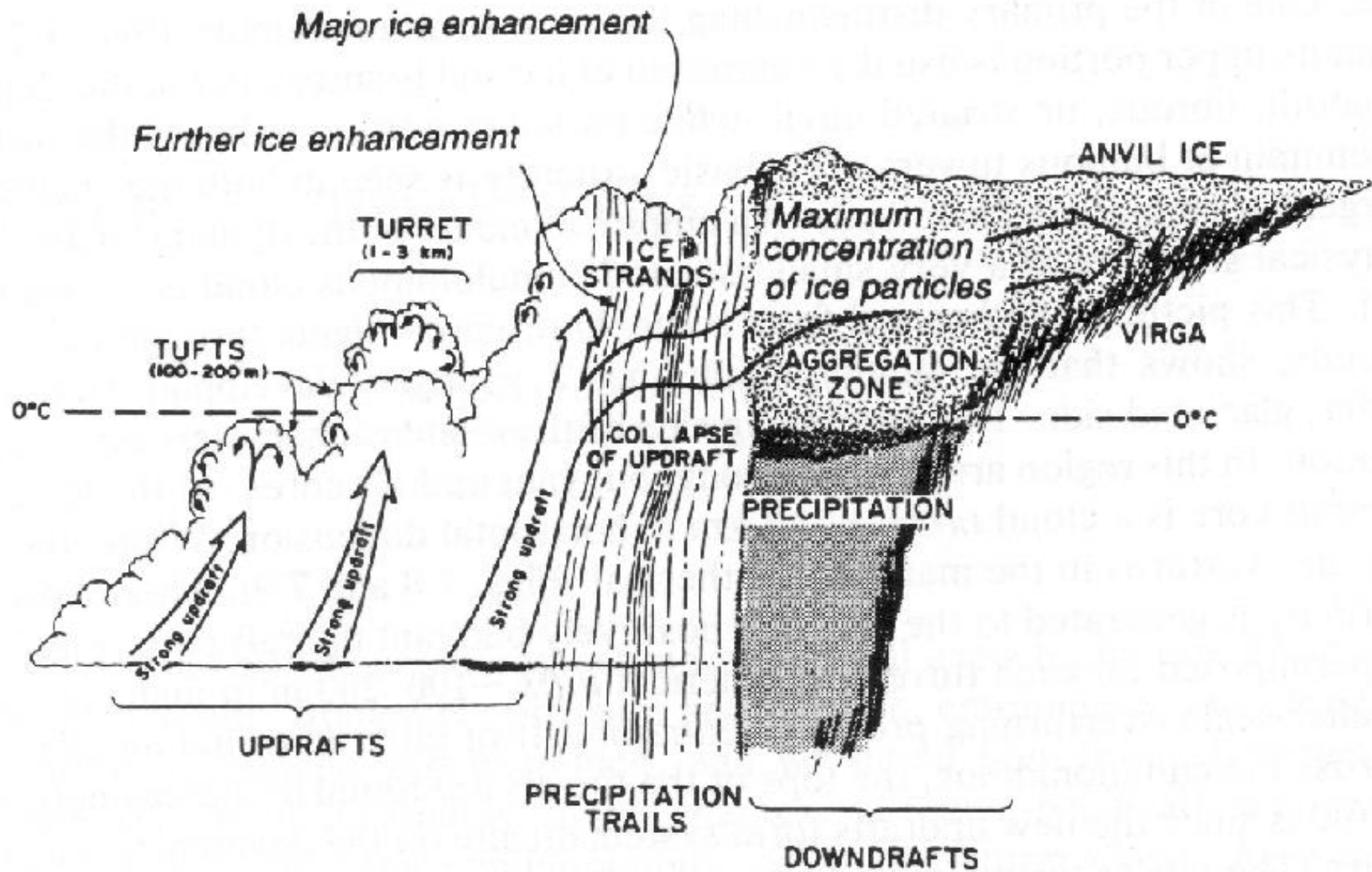


puissance (dB)



Validation sur les données réelles du cyclone Georges





Issues

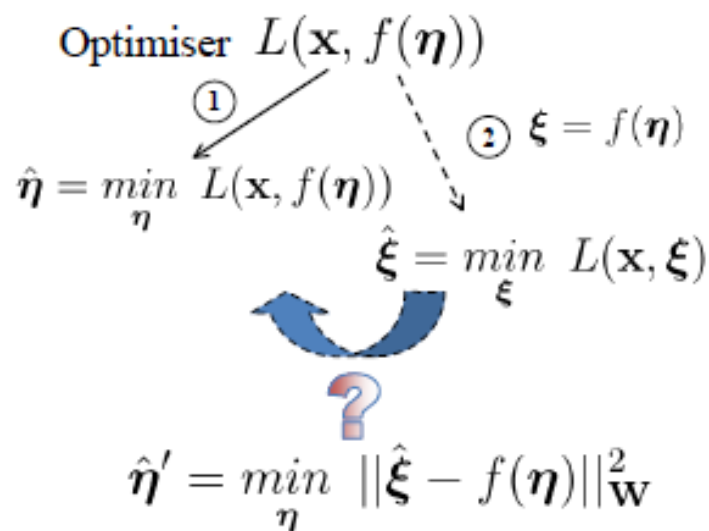
- Performance
- Computational complexity
- Robustness

Radar: Space Surveillance



- 5184 transmit elements
- 4660 receive elements

The extended invariance principle (EXIP)



- f , fonction injective ($\dim(\boldsymbol{\xi}) \geq \dim(\boldsymbol{\eta})$)
- Choix naturel : MCP.
- Choix du poids \mathbf{W} ?
- Comportement de $\hat{\boldsymbol{\eta}}'$?

EXIP [Stoica et al., 1989]

Si $f(\hat{\boldsymbol{\eta}}) \rightarrow \hat{\boldsymbol{\xi}}$, alors $\hat{\boldsymbol{\eta}}'$ converge en probabilité vers $\hat{\boldsymbol{\eta}}$
avec $\mathbf{W} = E \left[\frac{\partial^2 L(\mathbf{x}, \boldsymbol{\xi})}{\partial \boldsymbol{\xi} \partial \boldsymbol{\xi}^T} \right]$.

Estimation avec ajustement d'une matrice de covariance structurée

Modèle

$$\mathbf{x}(t) = A(\boldsymbol{\theta}) \mathbf{s}(t) + \mathbf{b}(t) \quad t = 1, \dots, T$$

Première étape

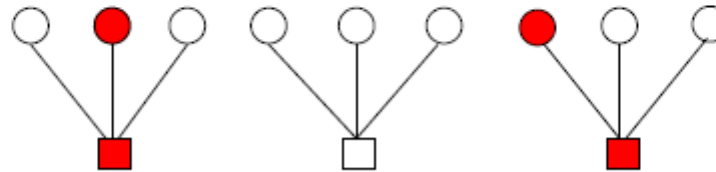
$$\hat{R} = \sum_{t=1}^T \mathbf{x}(t) \mathbf{x}(t)^H$$

Seconde étape

$$\left\{ \begin{array}{l} \hat{r} = \text{vec}(\hat{R}) \Rightarrow \hat{\gamma} = J\hat{r} \\ \gamma(\theta) = Jr(\theta) \end{array} \right\} \Rightarrow \hat{\theta} = \arg \min_{\theta} (\hat{\gamma} - \gamma(\theta))^H C^{-1} (\hat{\gamma} - \gamma(\theta))$$

Blood tests (Dorfman 1943)

N individuals. Probability of infection $p \ll 1$. Pool the tests:



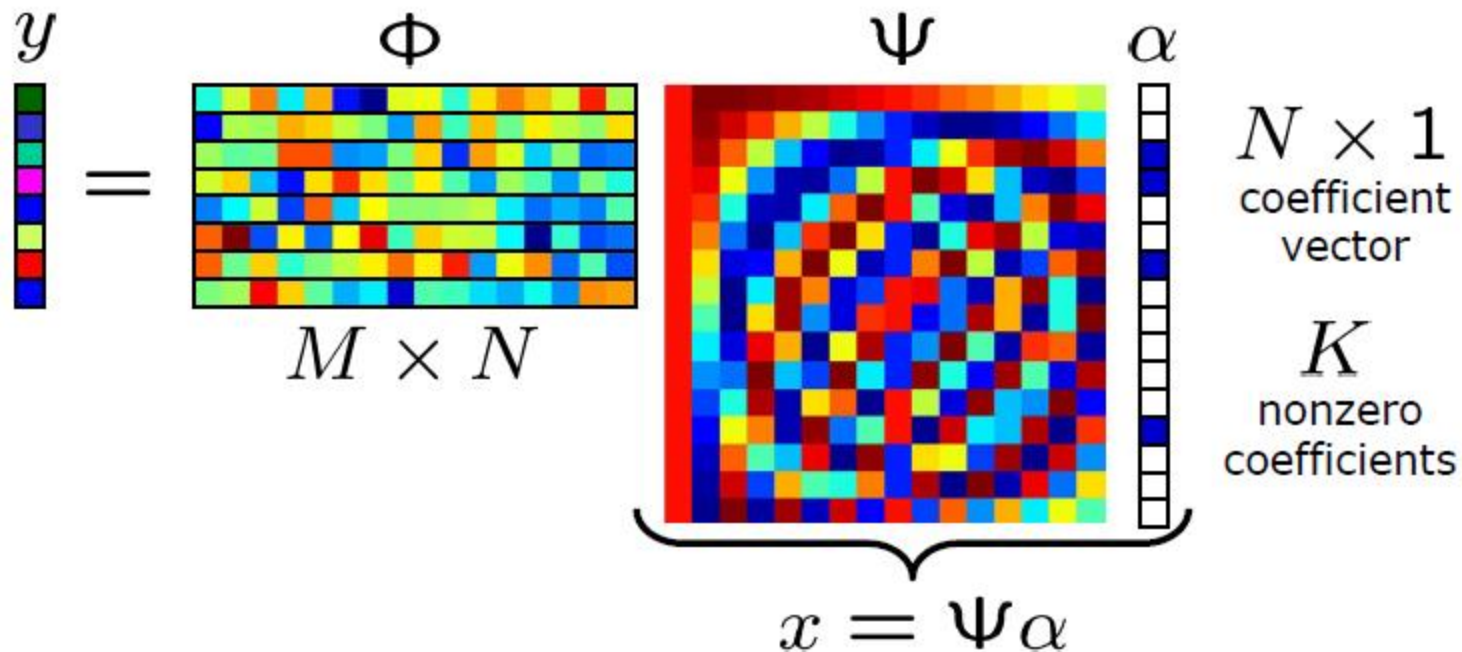
N/k groups of k persons, two-stage testing

$$\bar{T} = \frac{N}{k} + [1 - (1 - p)^k] \frac{N}{k} k$$

Minimal for $k \sim \frac{1}{\sqrt{p}}$, gives $\bar{T} \sim 2\sqrt{p}N$

CS Paradigm

- K -term quality from just $K \log(N)$ measurements



- Robust and widely applicable