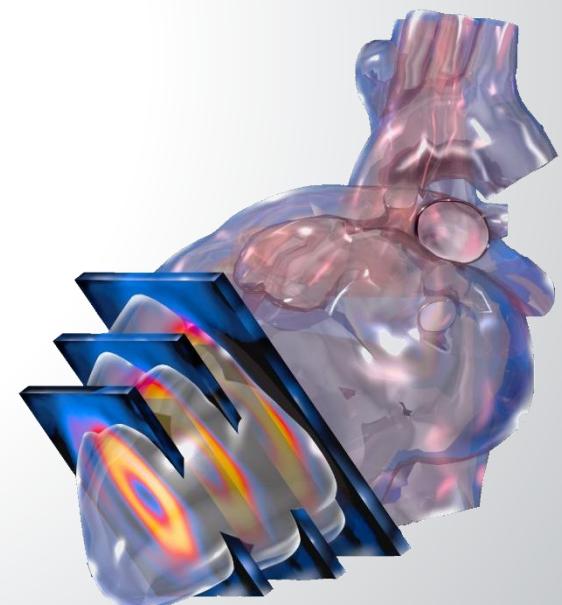


# MASTER PhyMed

GMPH308 - Physique de l'imagerie médicale

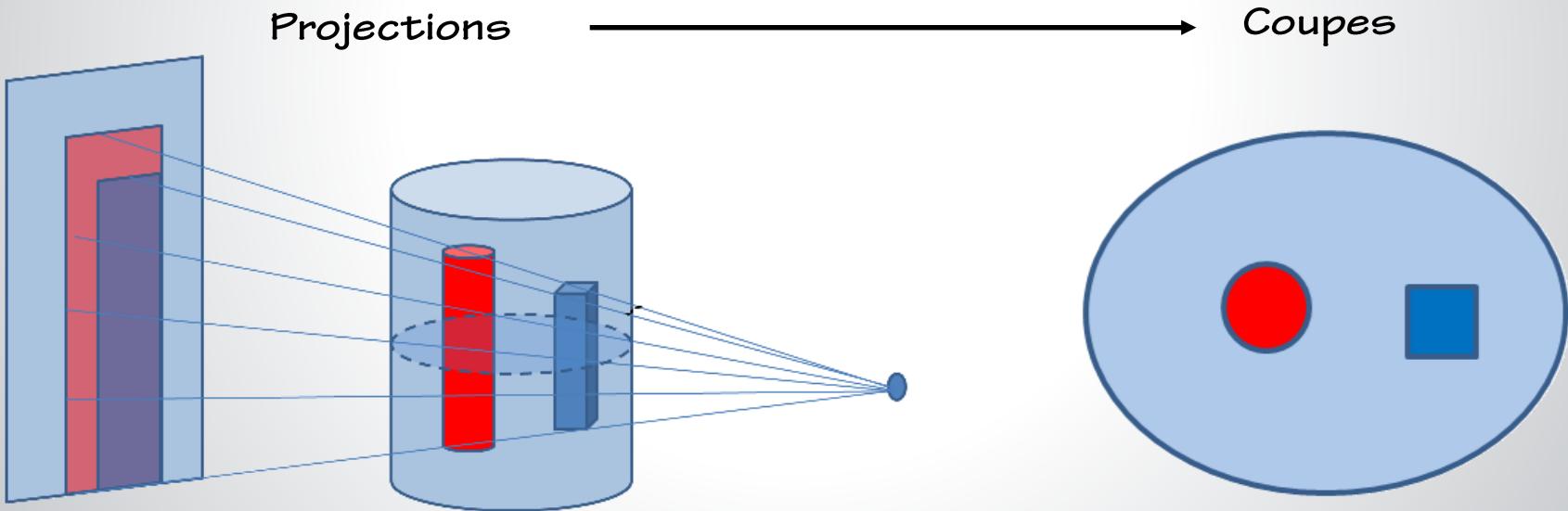
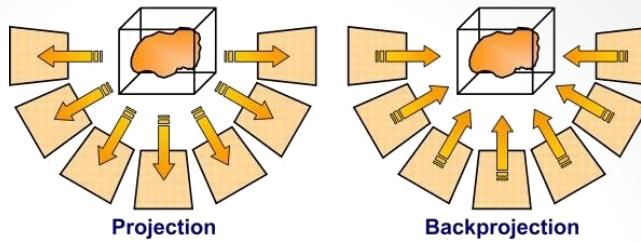
## TOMOGRAPHIE D'EMISSION



Fayçal Ben Bouallègue  
[faybenb@hotmail.com](mailto:faybenb@hotmail.com)  
<http://scinti.edu.umontpellier.fr>

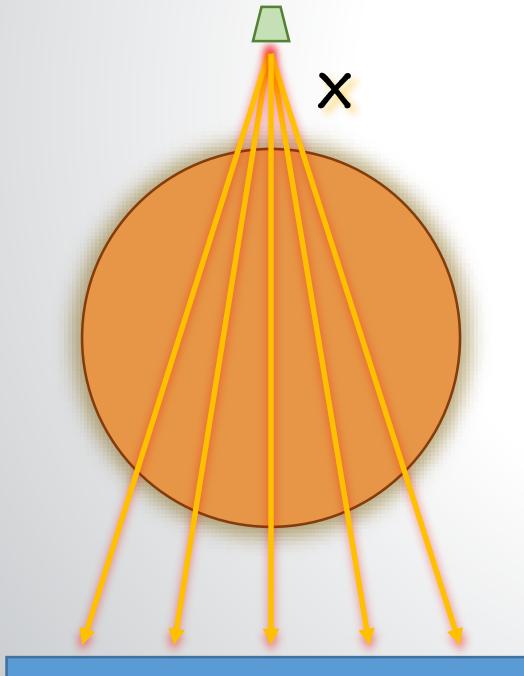


# Tomographie

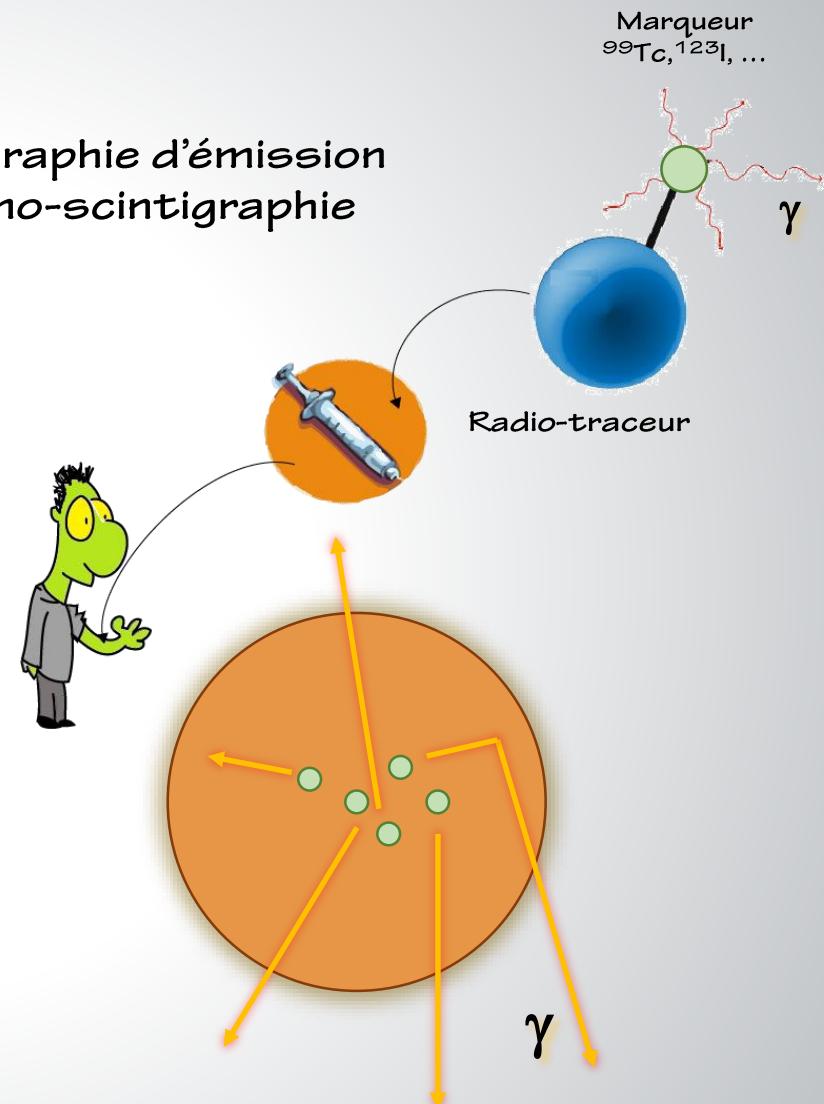


# Tomographie

Tomographie de transmission

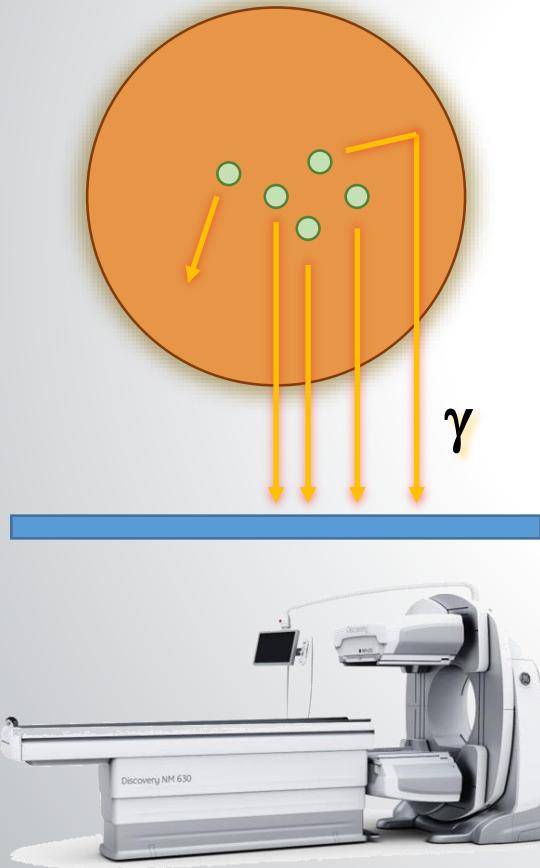


Tomographie d'émission  
= tomo-scintigraphie

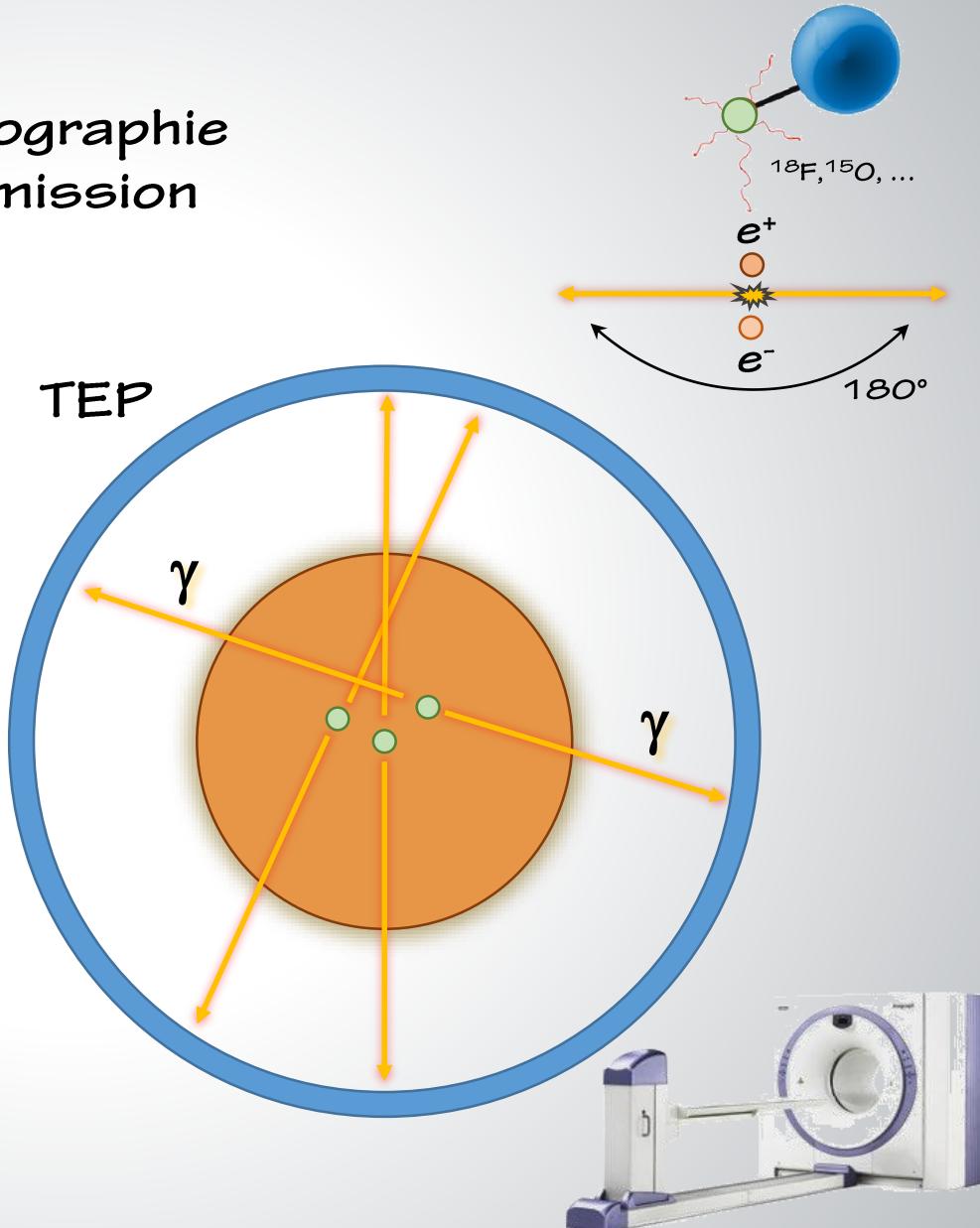


# Tomographie

TEMP = SPECT

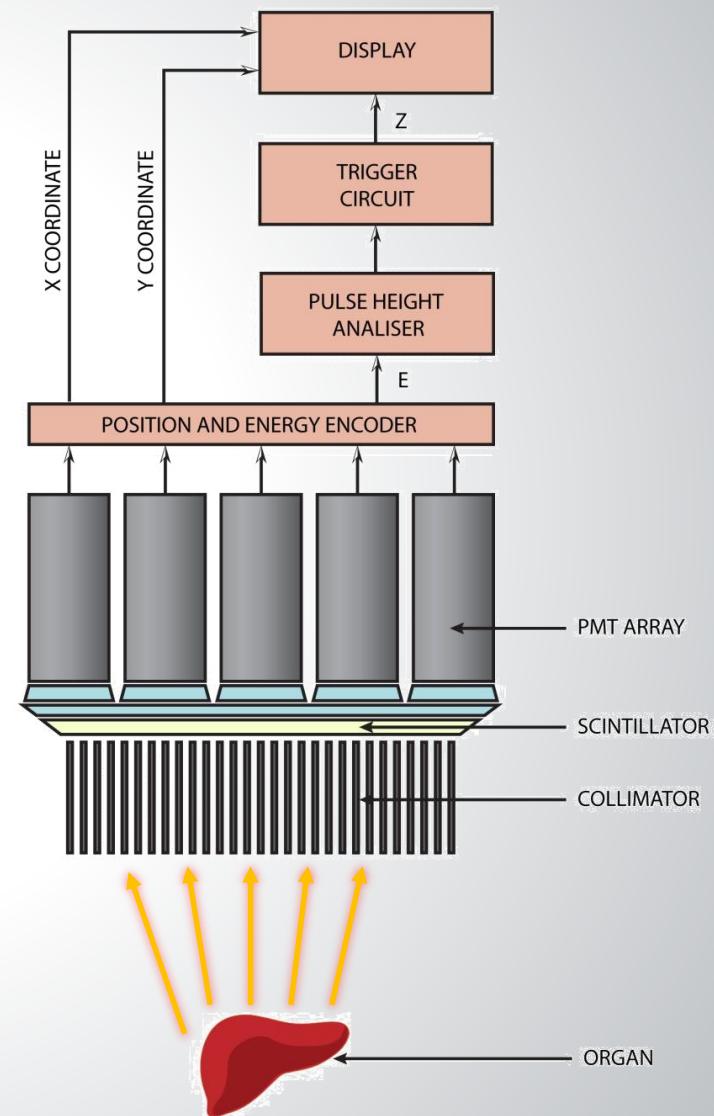
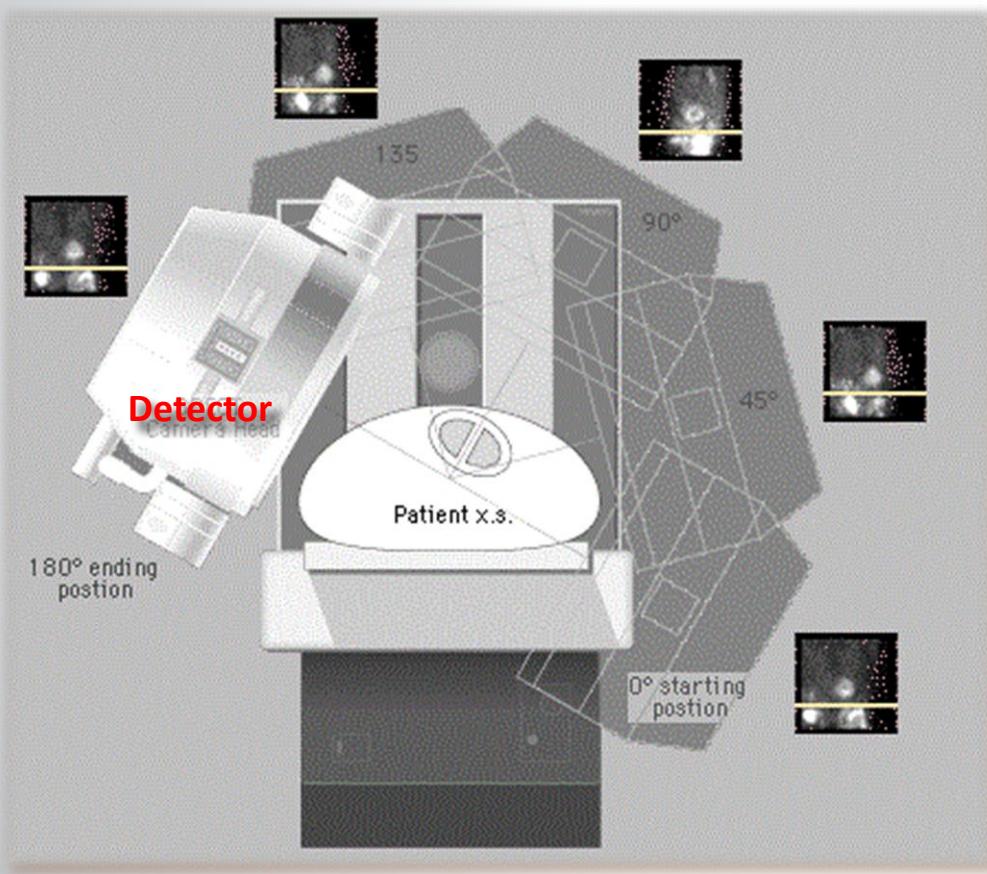


Tomographie  
d'émission



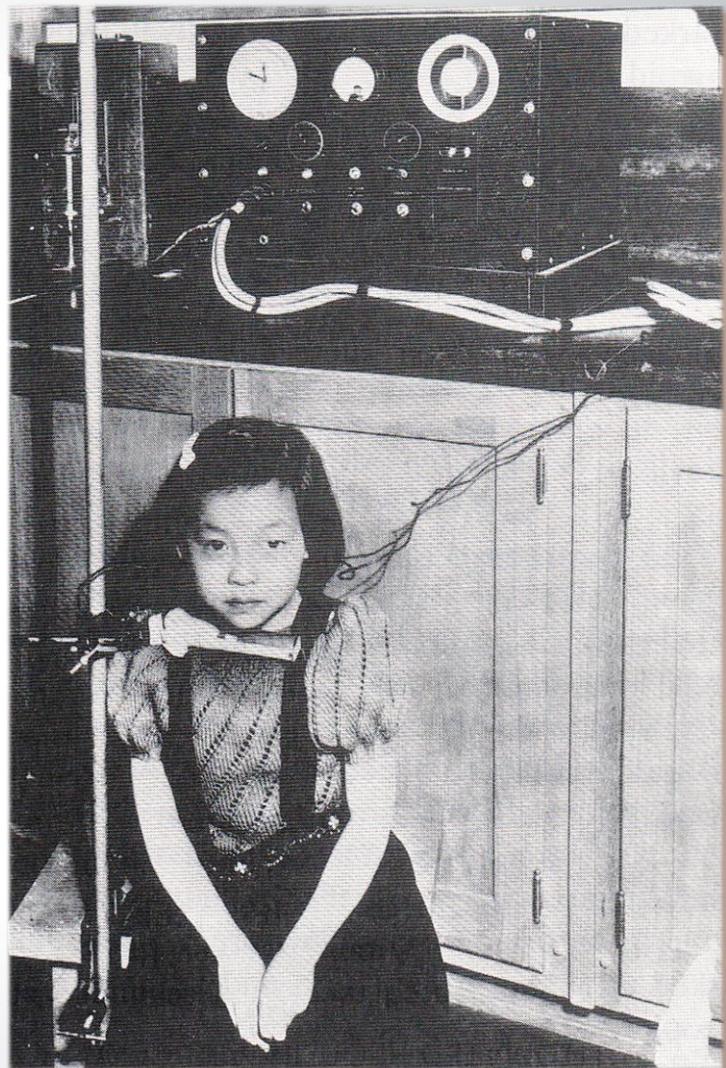
# TEMP - acquisition

## Gamma caméra d'Anger



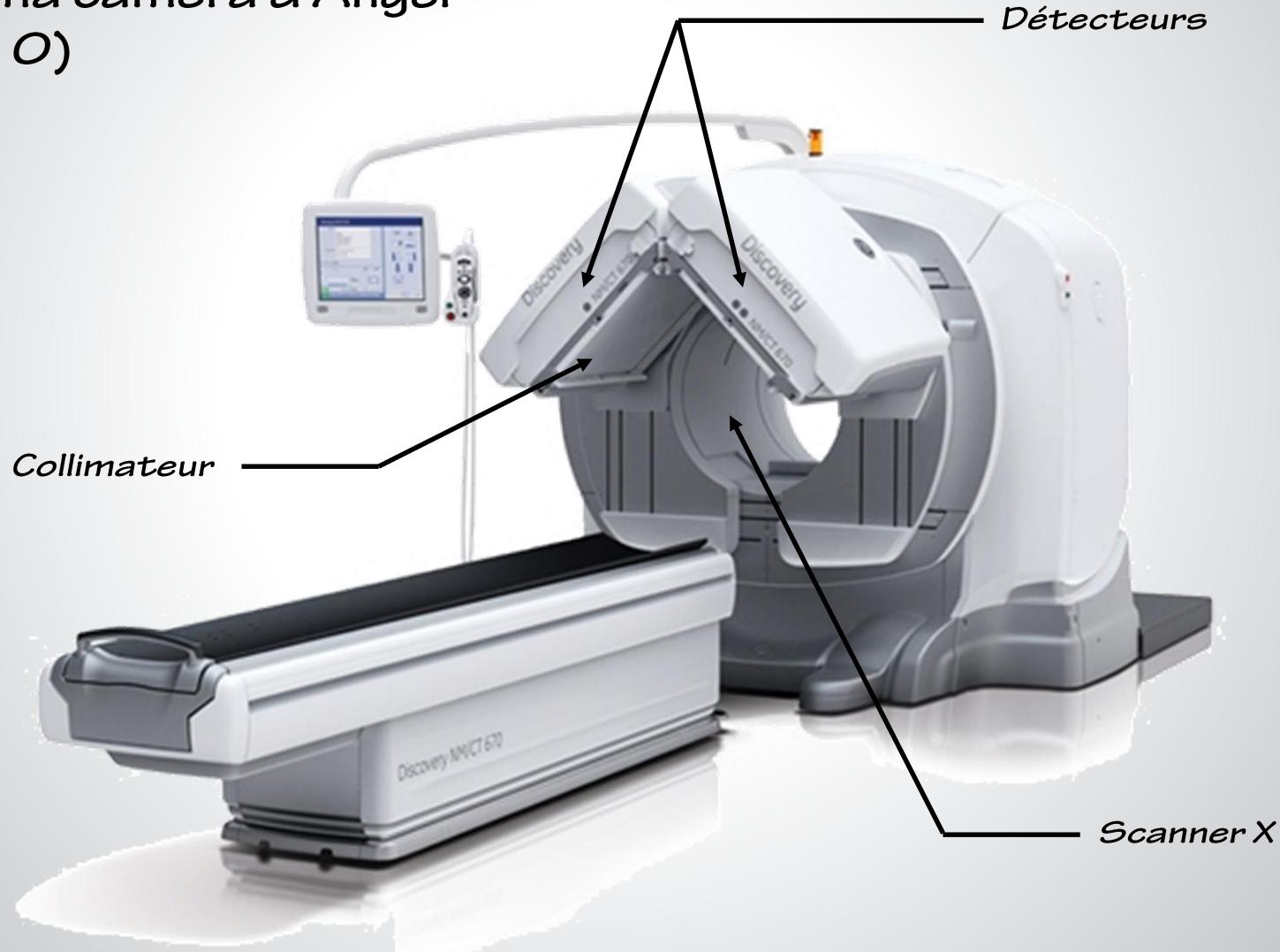
# TEMP - acquisition

Gamma caméra d'Anger  
(1958)



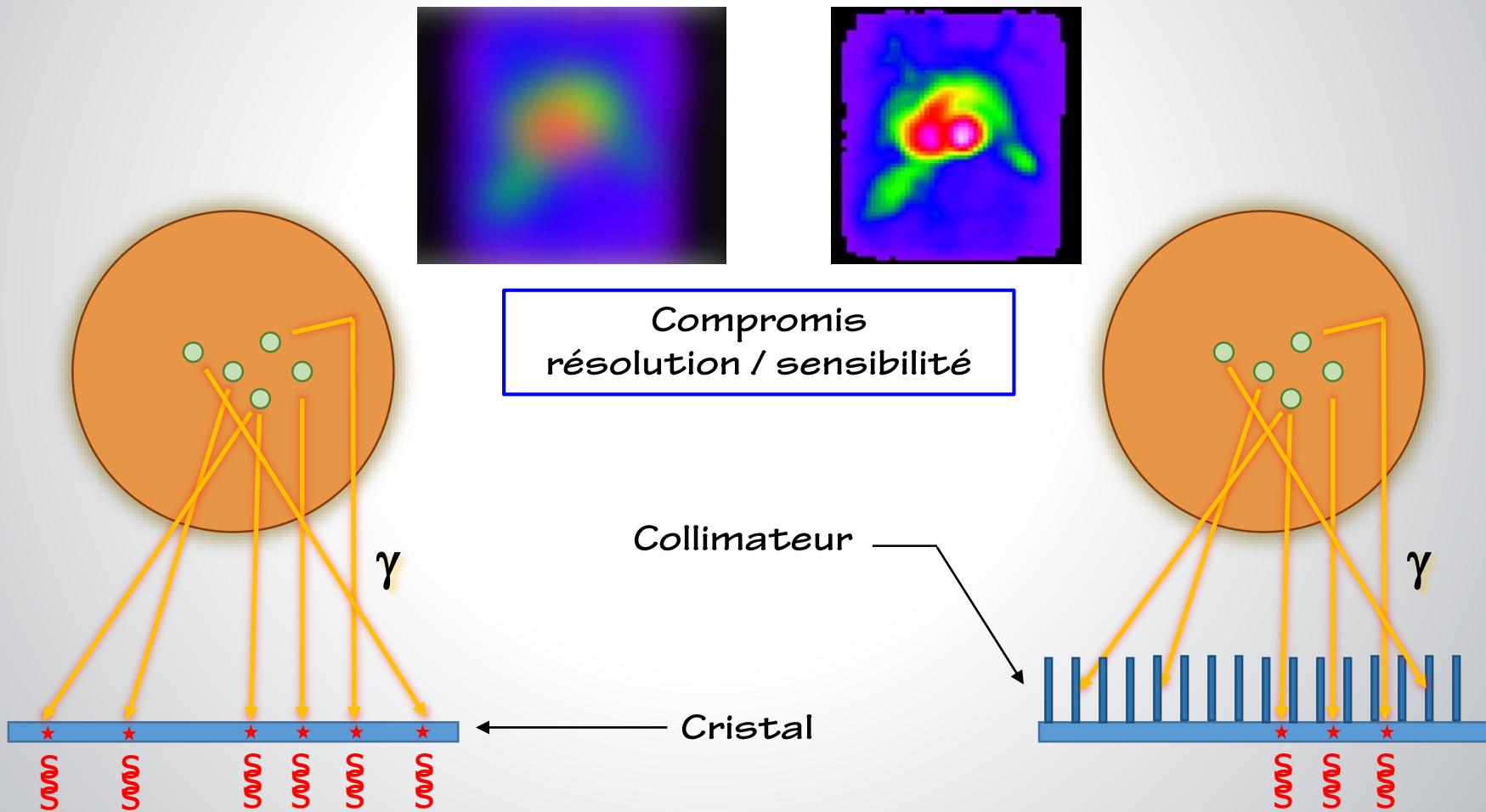
# TEMP - acquisition

Gamma caméra d'Anger  
(2010)



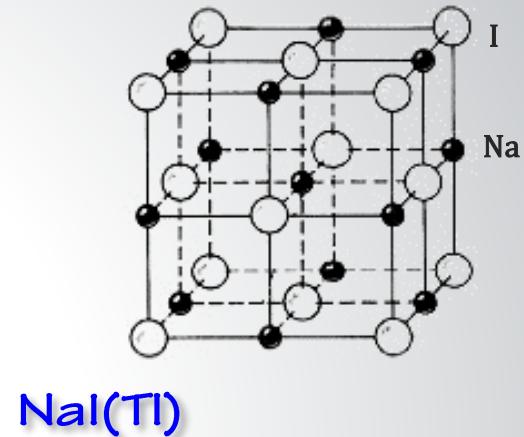
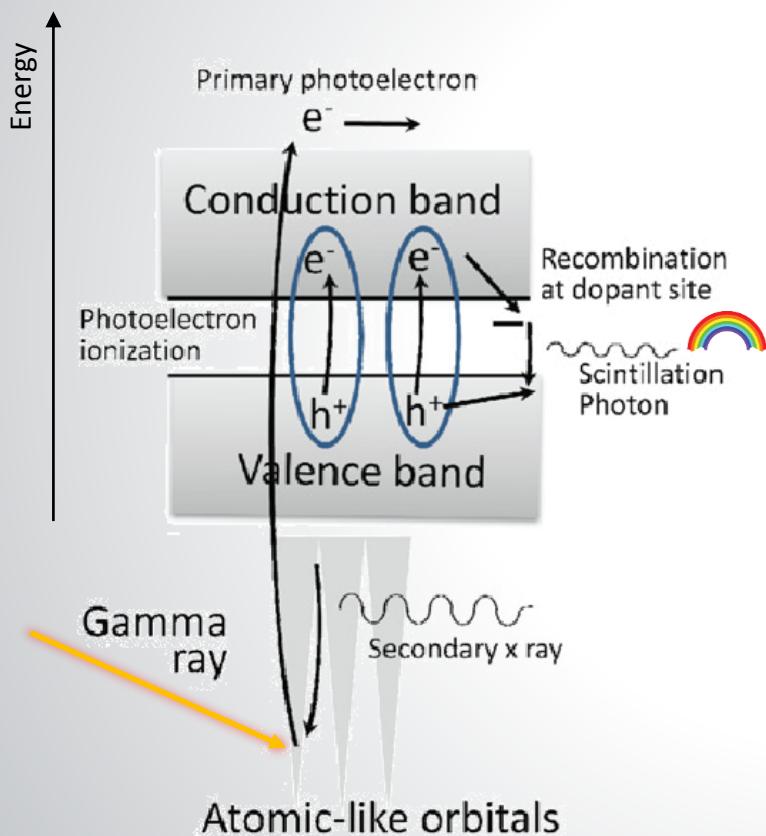
# TEMP - acquisition

## ■ Collimation

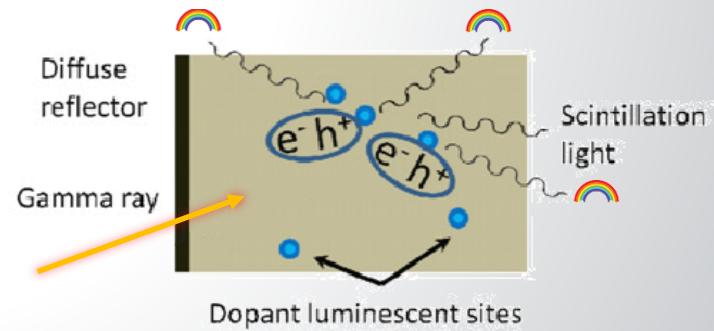


# TEMP - acquisition

## ■ Scintillation

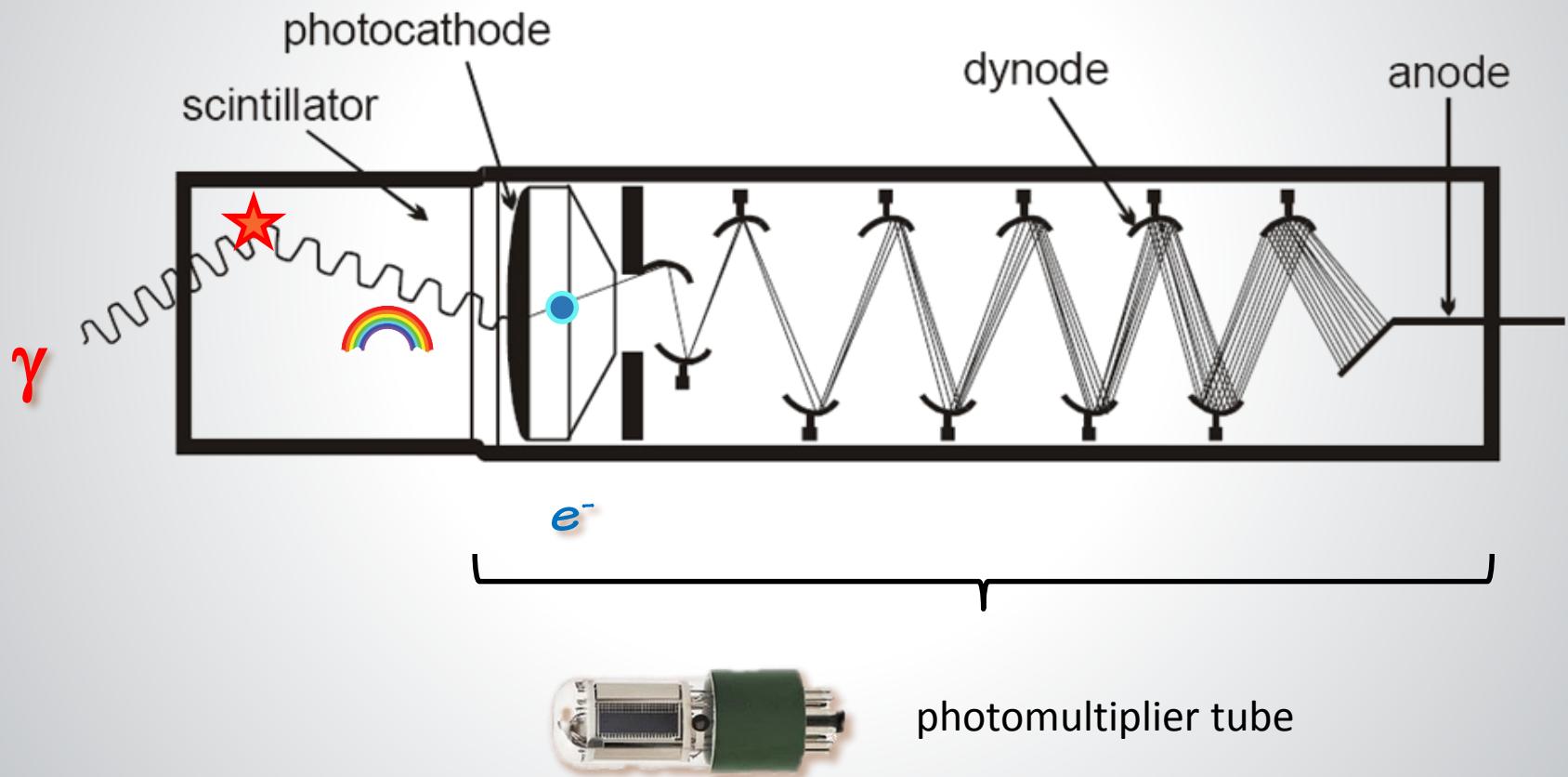


NaI(Tl)



# TEMP - acquisition

## ■ Amplification



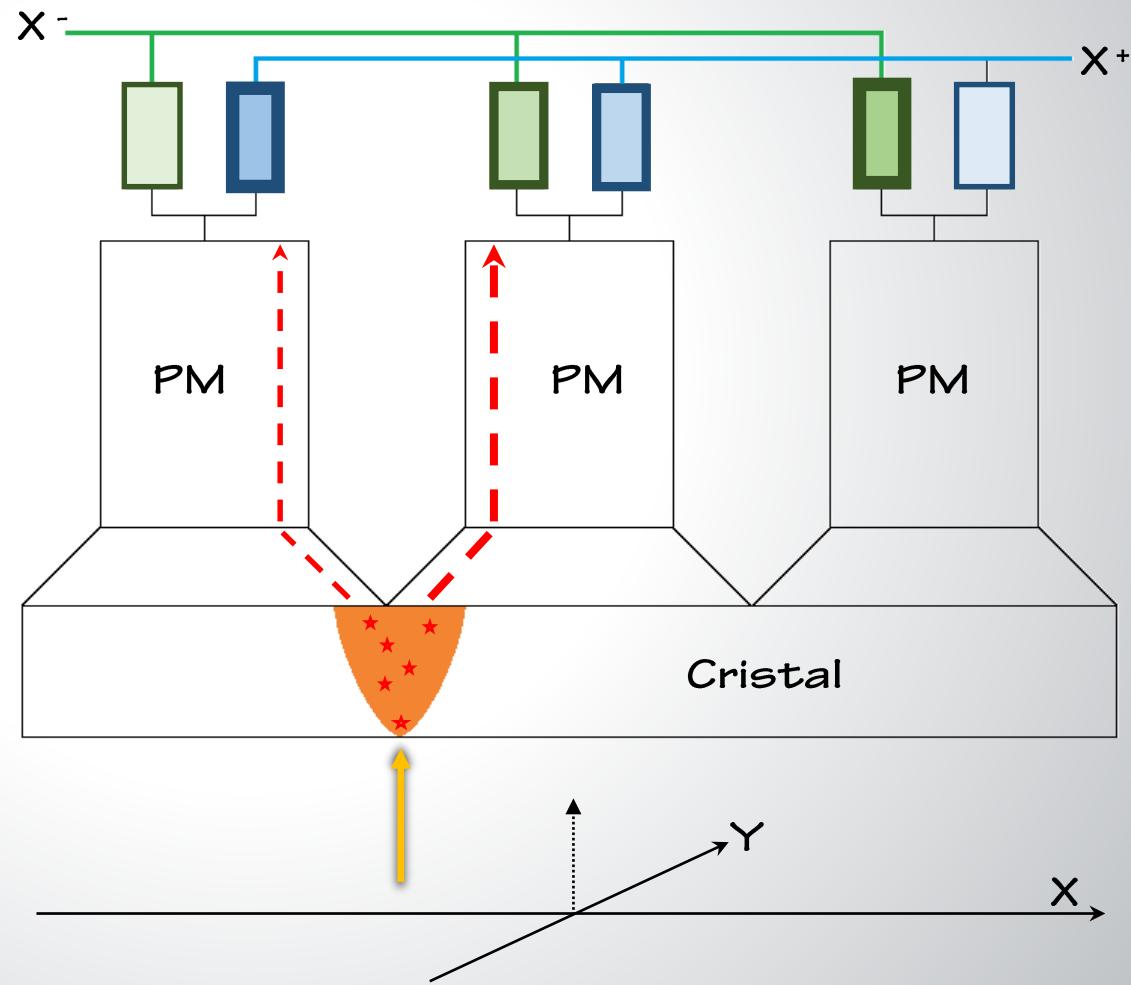
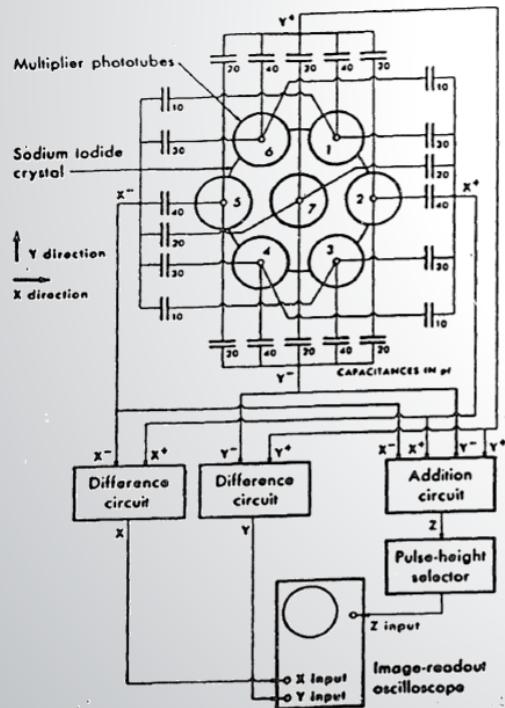
# TEMP - acquisition

## ■ Localisation

$$X = X^+ - X^-$$

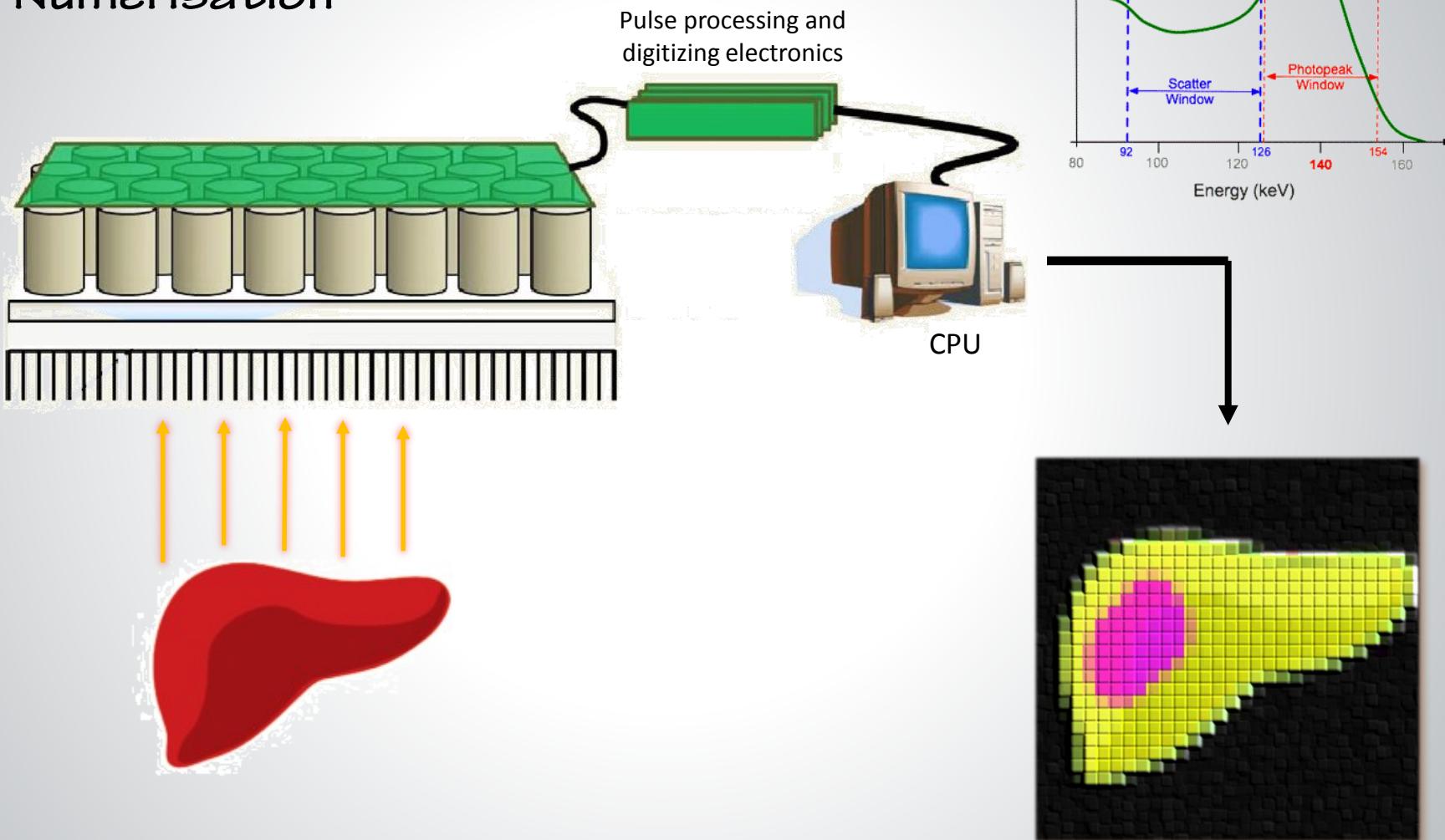
$$Y = Y^+ - Y^-$$

$$E = X^+ + X^- + Y^+ + Y^-$$

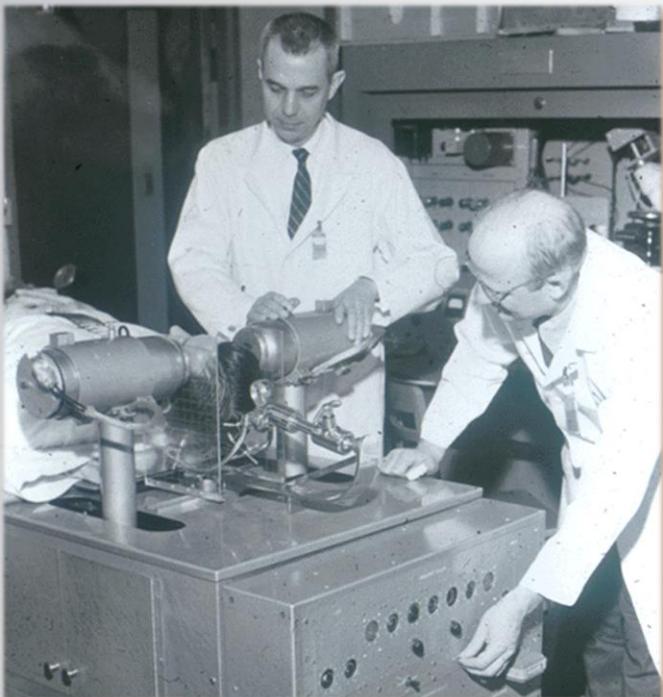


# TEMP - acquisition

## ■ Numérisation



# TEP - acquisition



G Brownell & C Burnham  
Boston 1952

## The New England Journal of Medicine

Copyright, 1951, by the Massachusetts Medical Society

Volume 245

DECEMBER 6, 1951

Number 23

### THE USES OF NUCLEAR DISINTEGRATION IN THE DIAGNOSIS AND TREATMENT OF BRAIN TUMOR\*

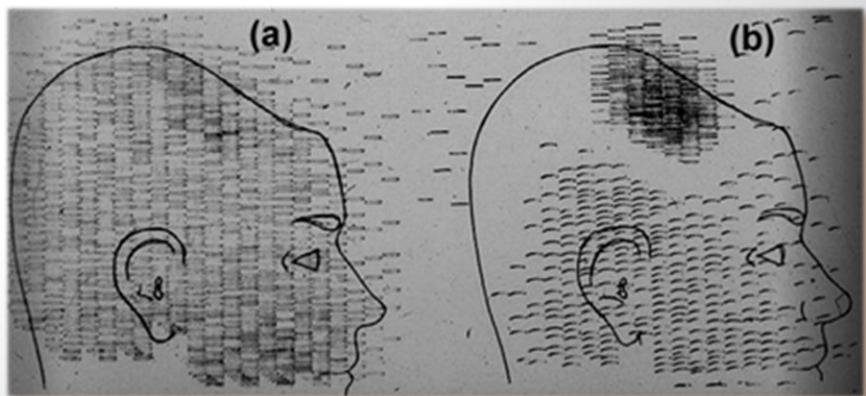
WILLIAM H. SWEET, M.D.†

BOSTON

**I**N THE utilization of isotopes to aid in the clinical management of intracranial tumors that has been developed at this hospital in the past few years, we have been aided by many workers. The time at which an elaborate addition to the hospital's investigative facilities is brought into action is perhaps a suitable time to draw attention to the diversity of talents that has been required for making some headway in such a limited field as that of brain tumors.

ascertain by the counting rate when neoplasm is entered and where its limits are.

Such a probe counter was first designed by the physicist Dr. Charles Robinson, then of Wisconsin. Dr. Solomon promptly secured the aid of Dr. Robinson and his counter, which device we used in man in time to send a telegram with the data to

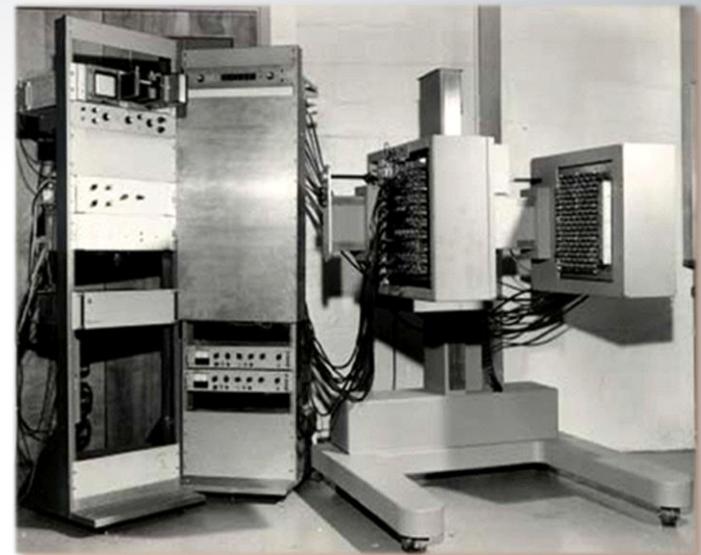


# TEP - acquisition

Multidétecteur  
Mode tomographique

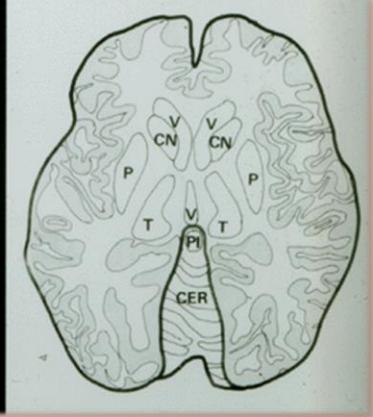
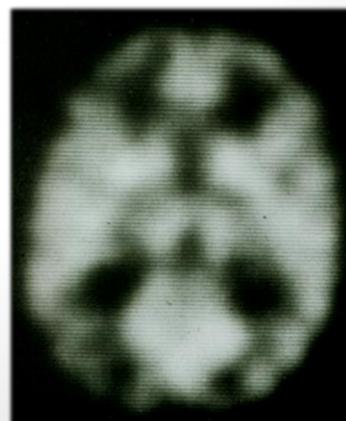


1975



1970

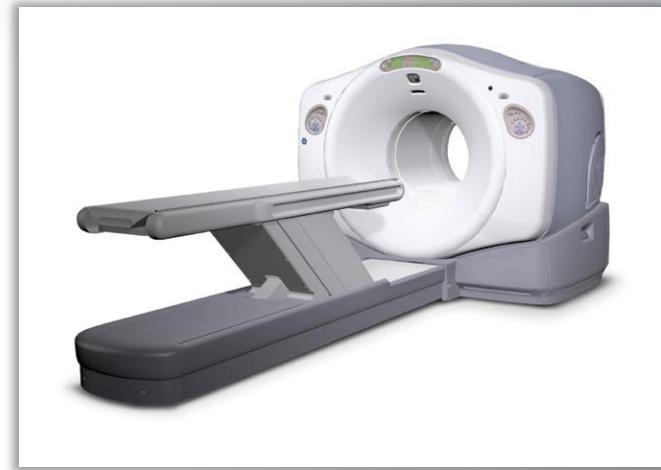
$^{18}\text{FDG}$   
1976



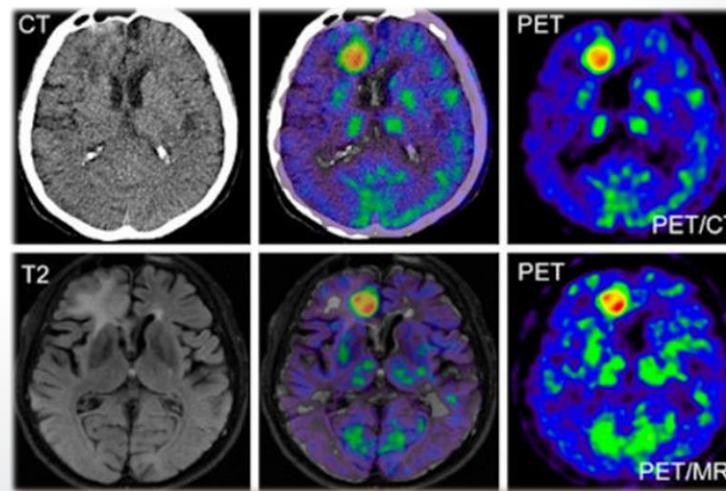
# TEP - acquisition



Anneau de détecteurs  
1980

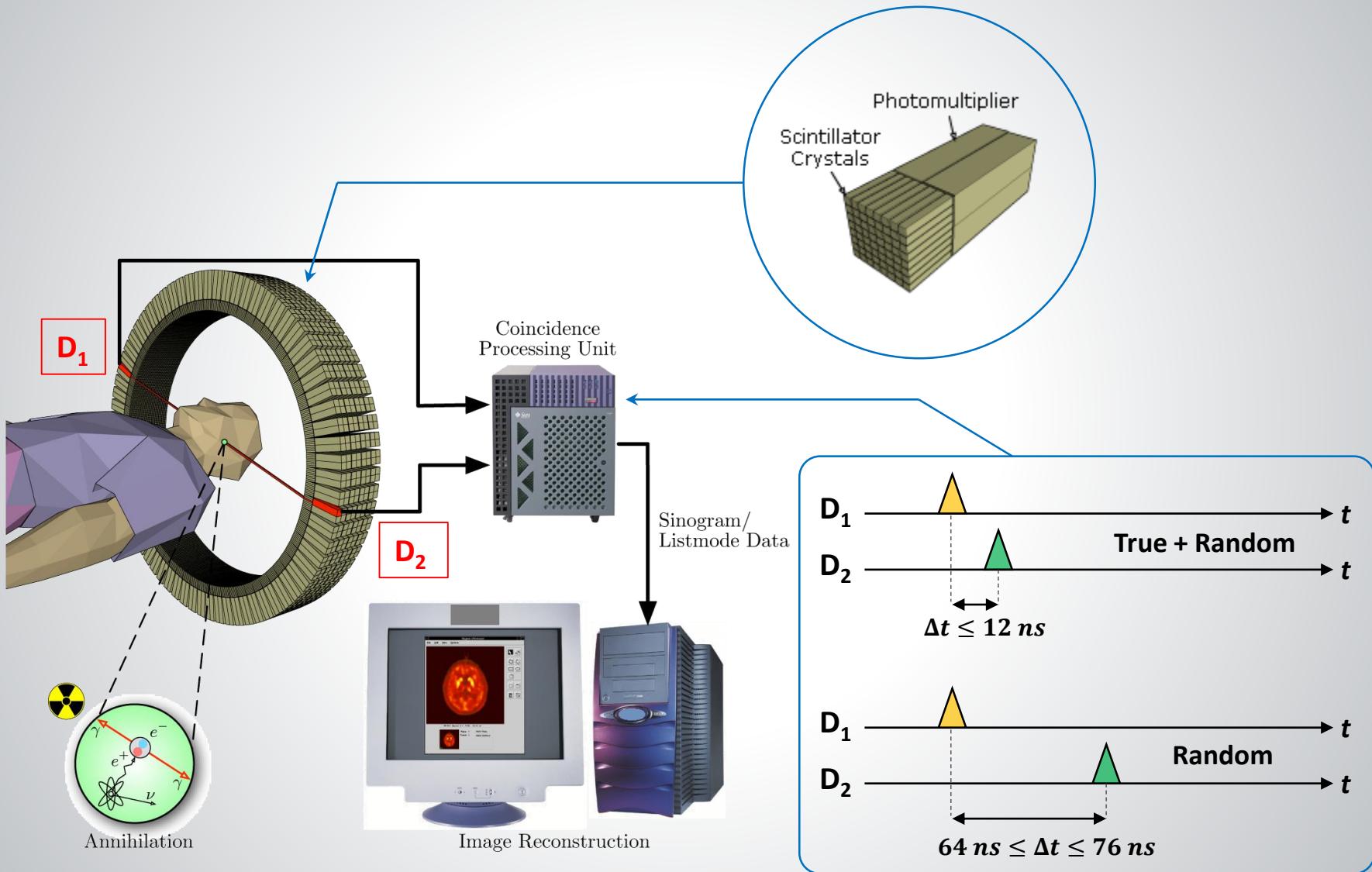


TEP-MR  
2010

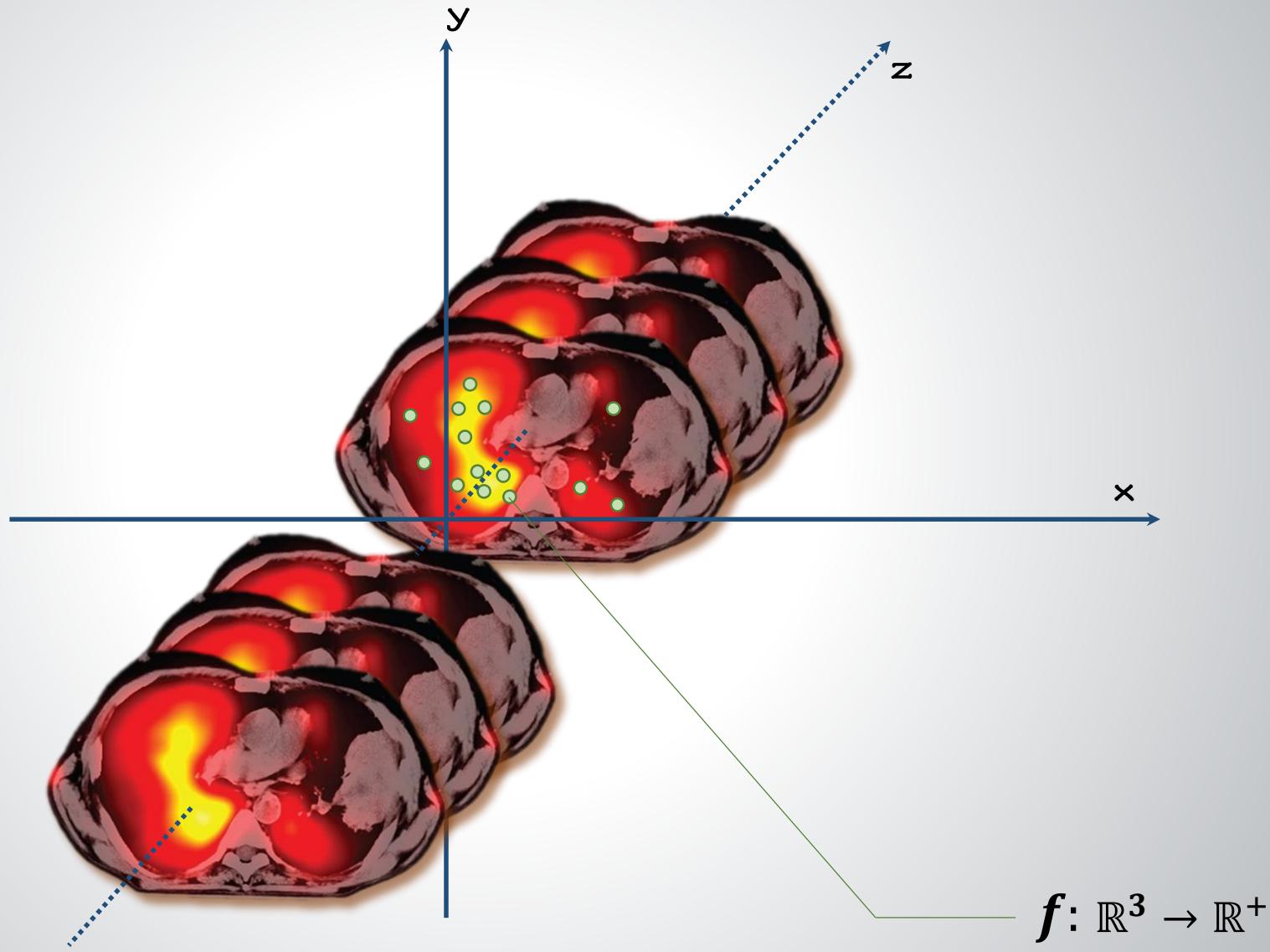


TEP-CT  
1998

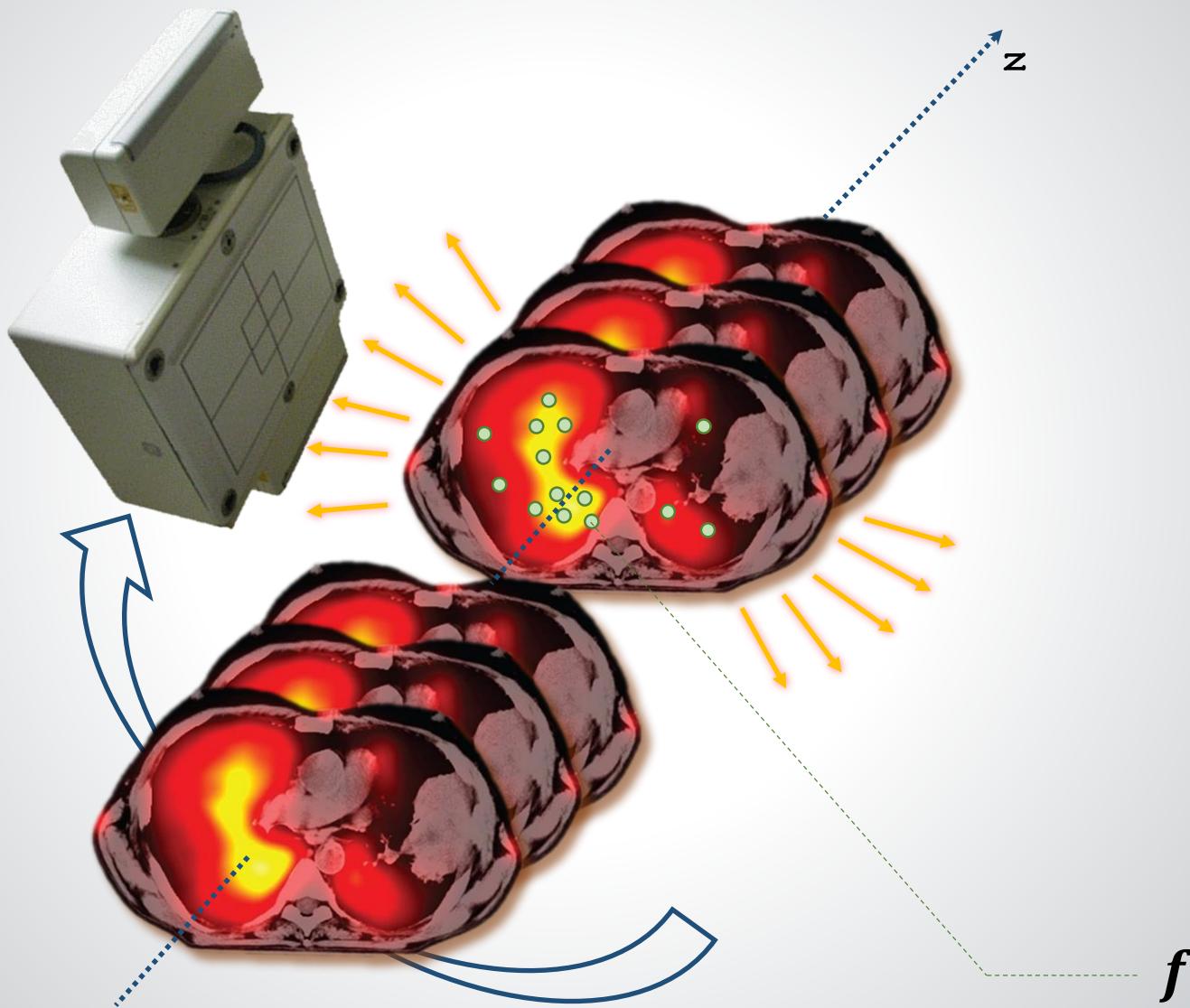
# TEP - acquisition



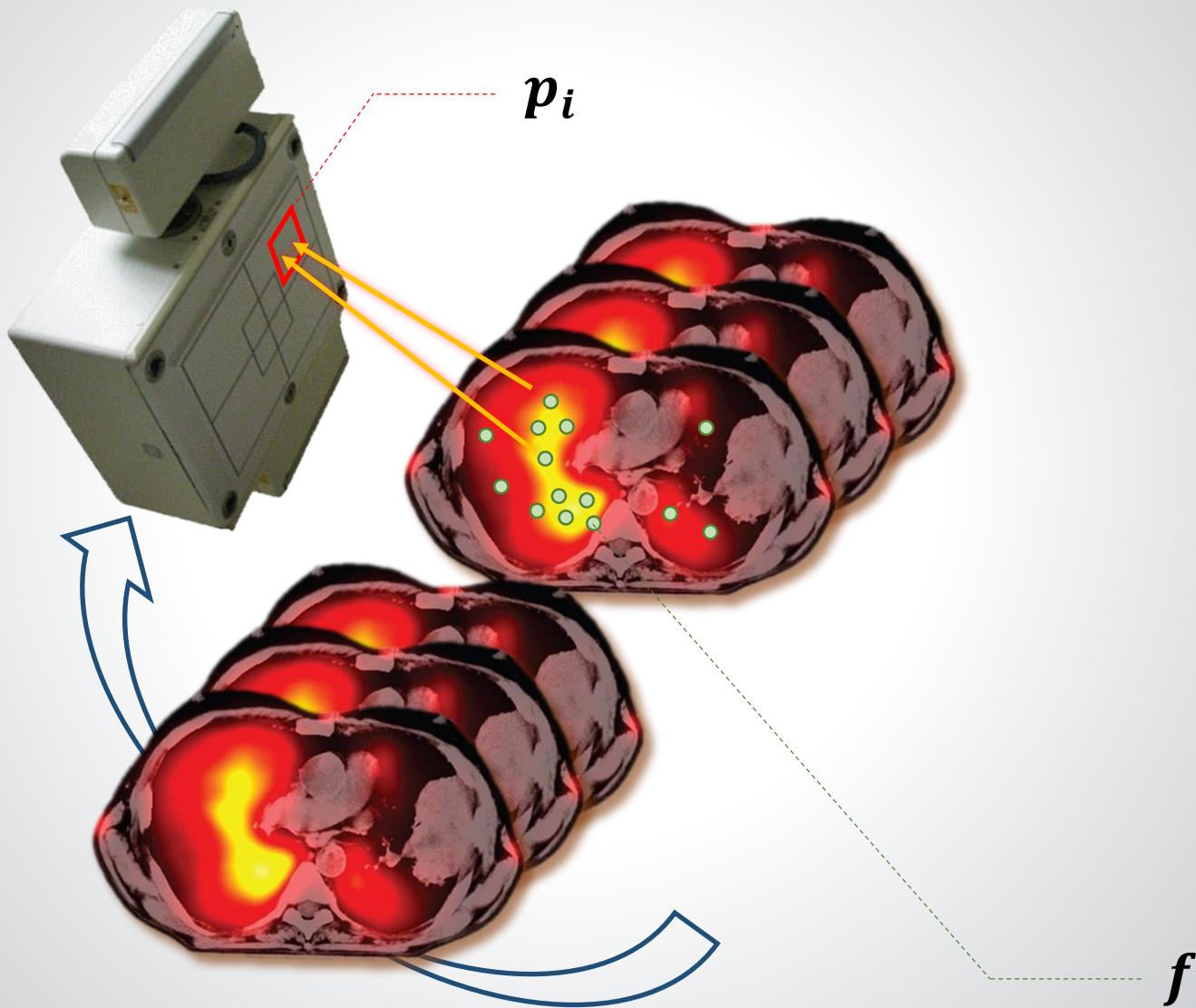
# Problème tomographique



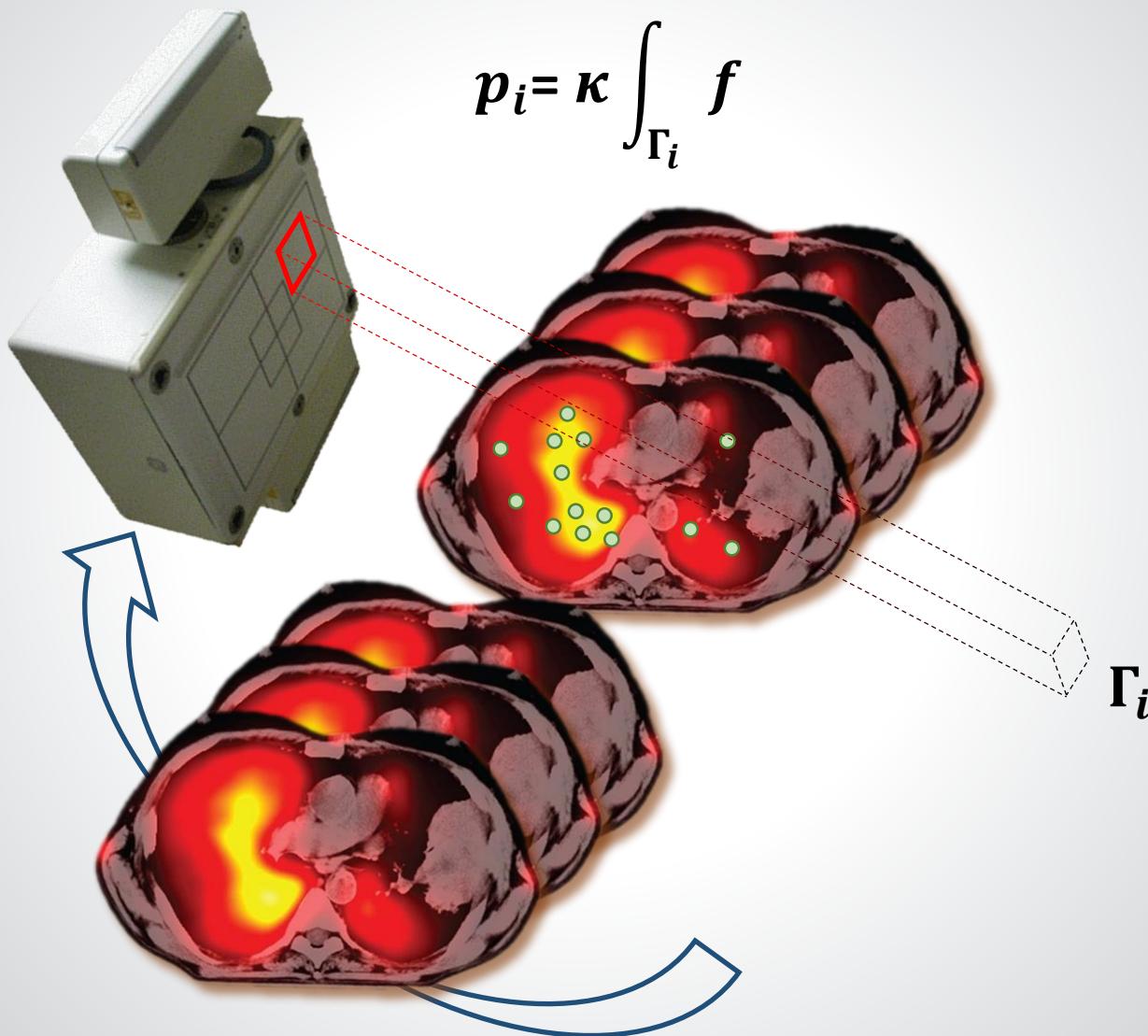
# Problème tomographique



# Problème tomographique

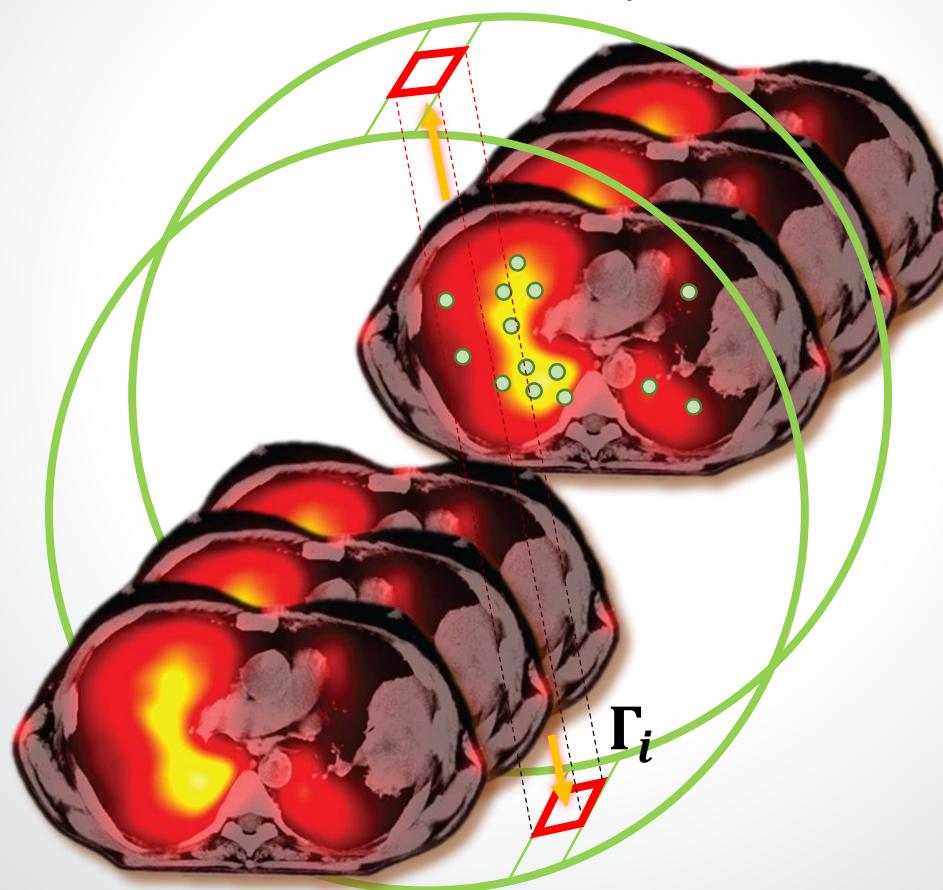


# Problème tomographique

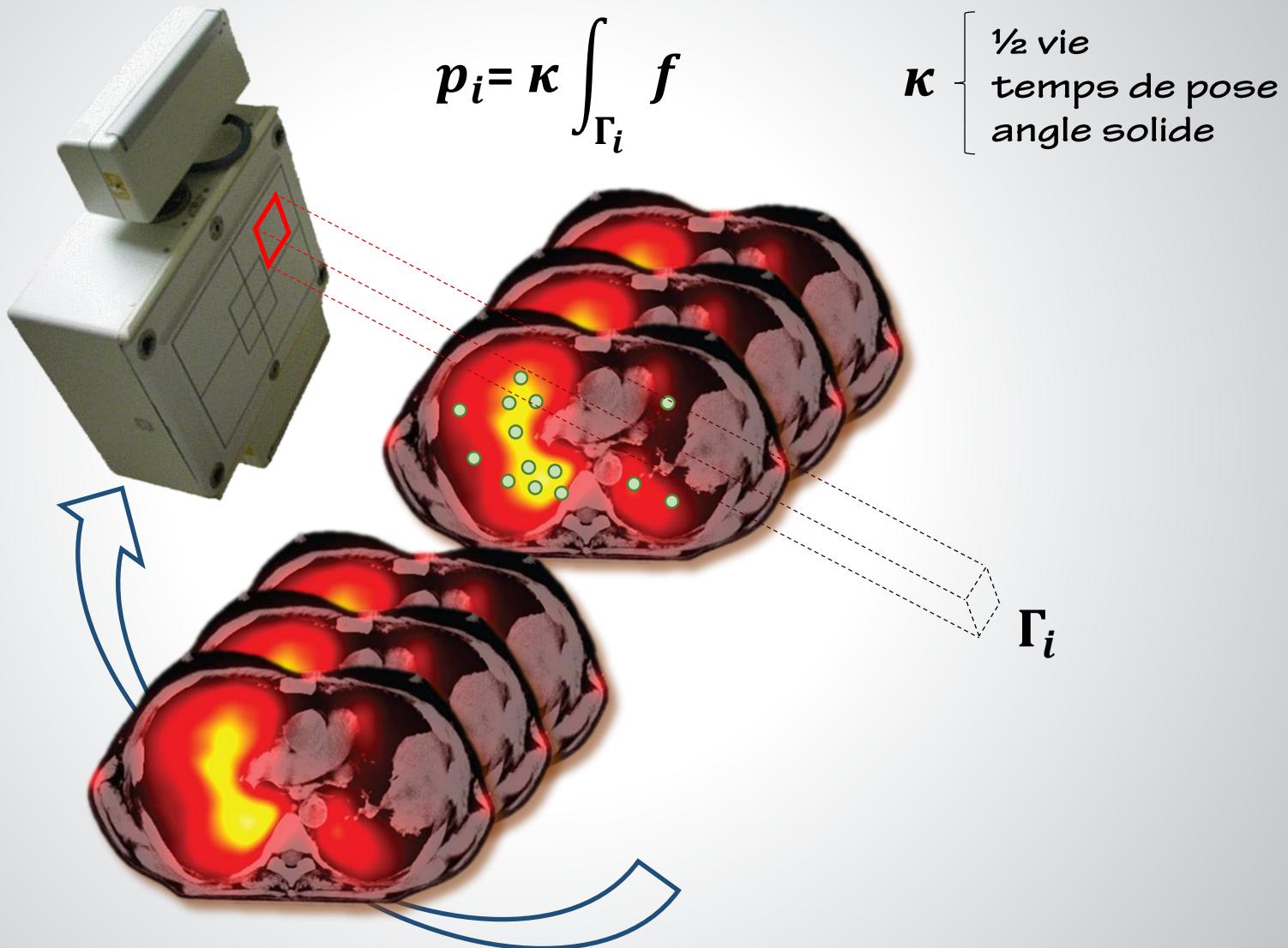


# Problème tomographique

$$p_i = \kappa \int_{\Gamma_i} f$$

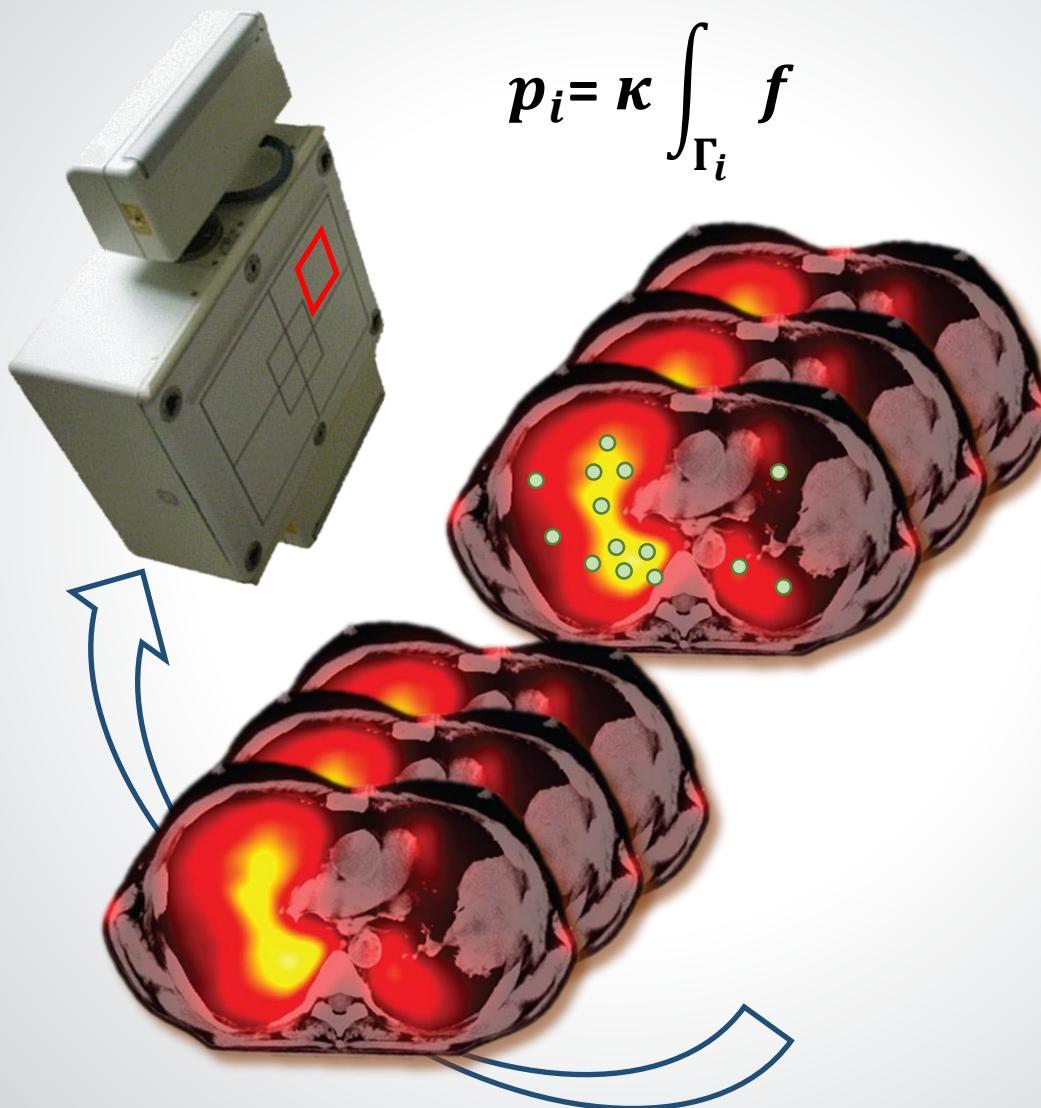


# Problème tomographique



# Problème tomographique

$$p_i = \kappa \int_{\Gamma_i} f$$

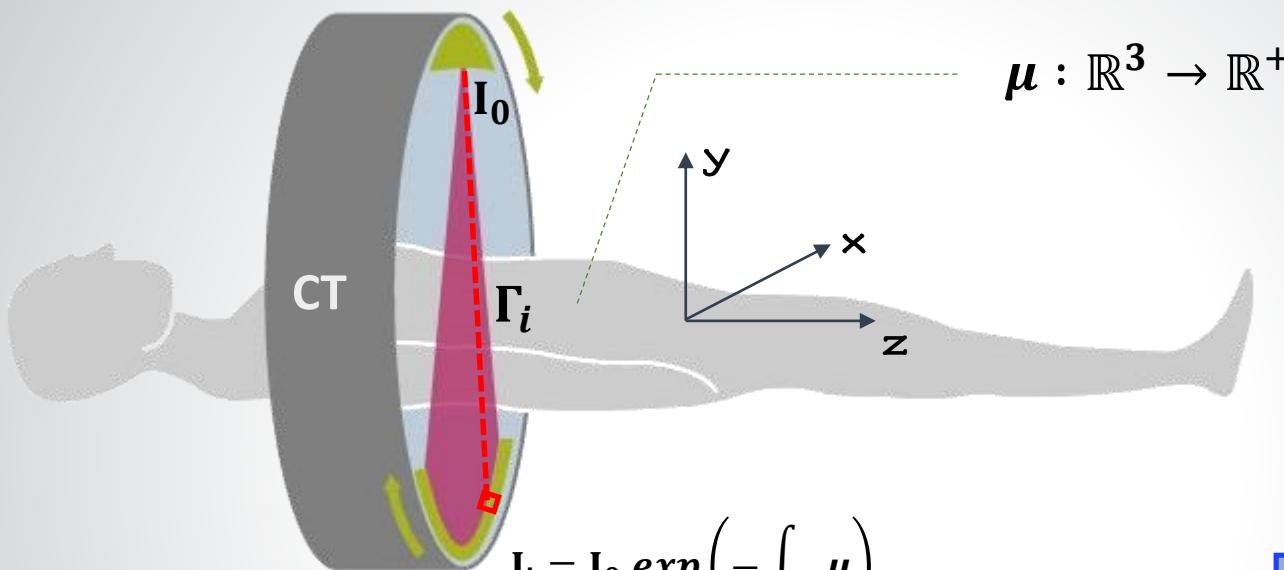


$$p_i \quad (i = 1 \dots N)$$



$$f$$

# Problème tomographique



$$\mu : \mathbb{R}^3 \rightarrow \mathbb{R}^+$$

$$I_i = I_0 \exp\left(-\int_{\Gamma_i} \mu\right)$$

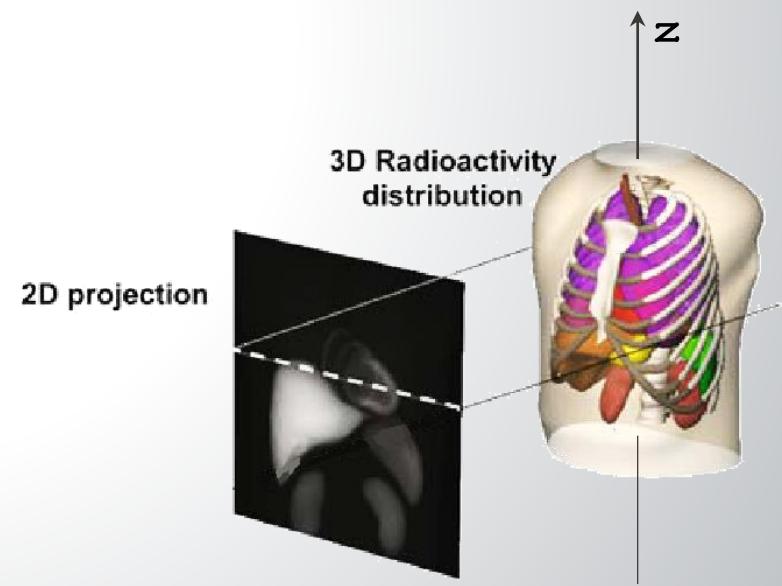
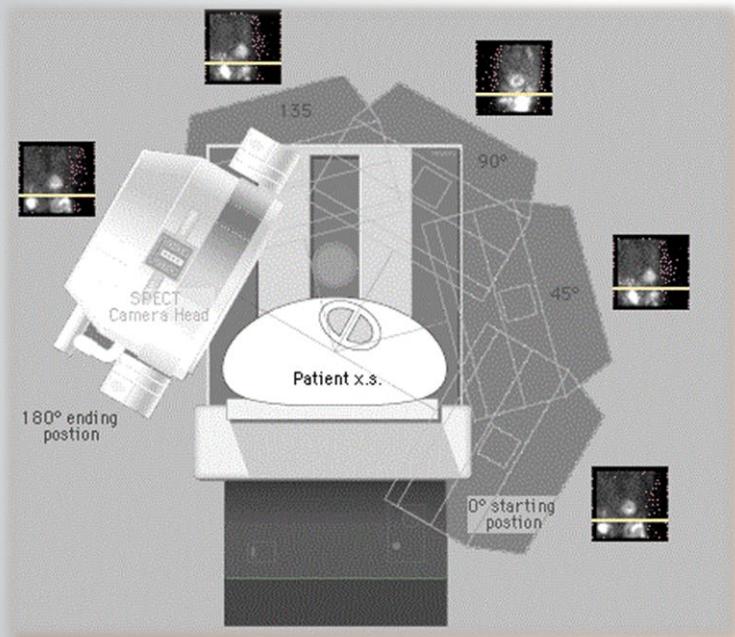
$$p_i = -\ln\left(\frac{I_i}{I_0}\right) = \int_{\Gamma_i} \mu$$

$$p_i \quad (i = 1 \dots N)$$

$$\downarrow ? \downarrow \\ \mu$$

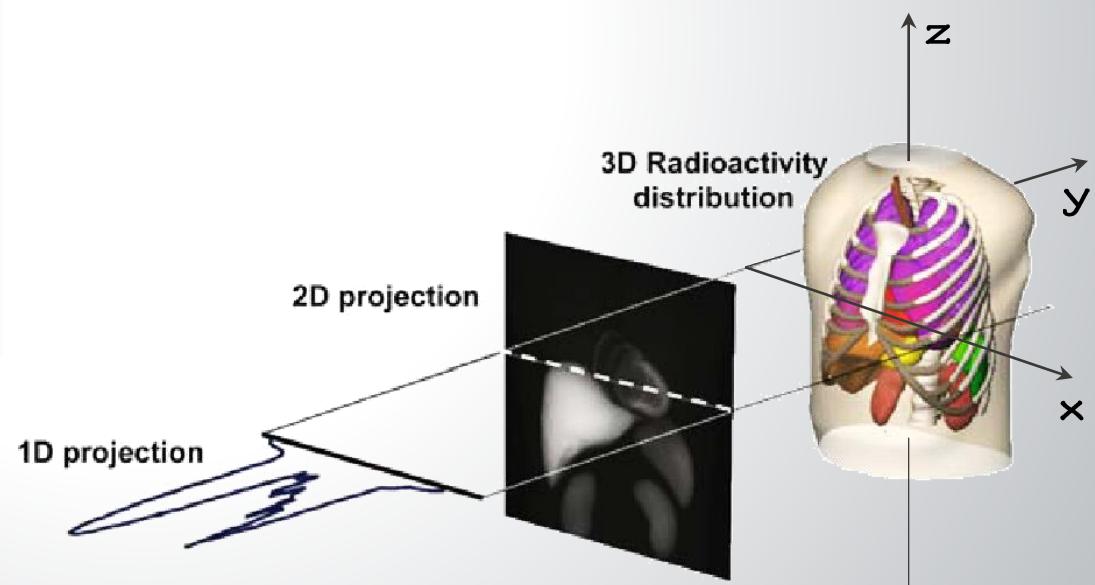
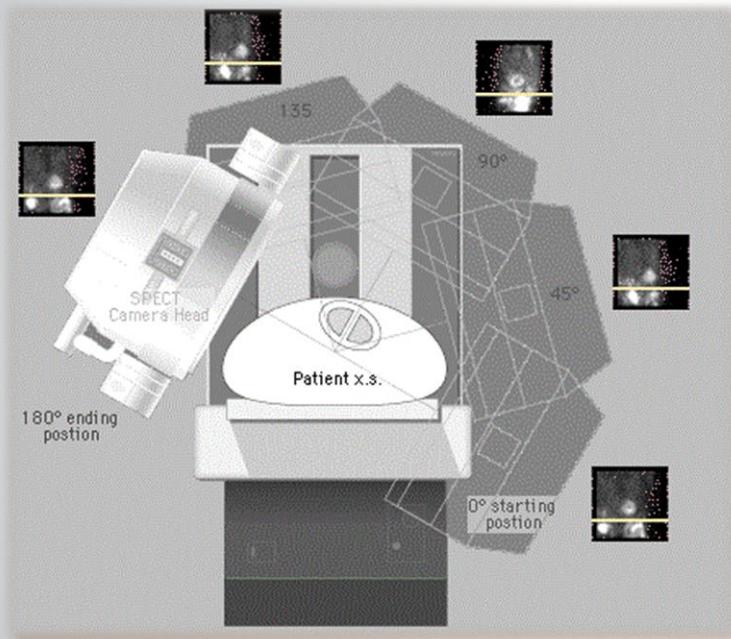
# Reconstruction

## ■ Modèle analytique



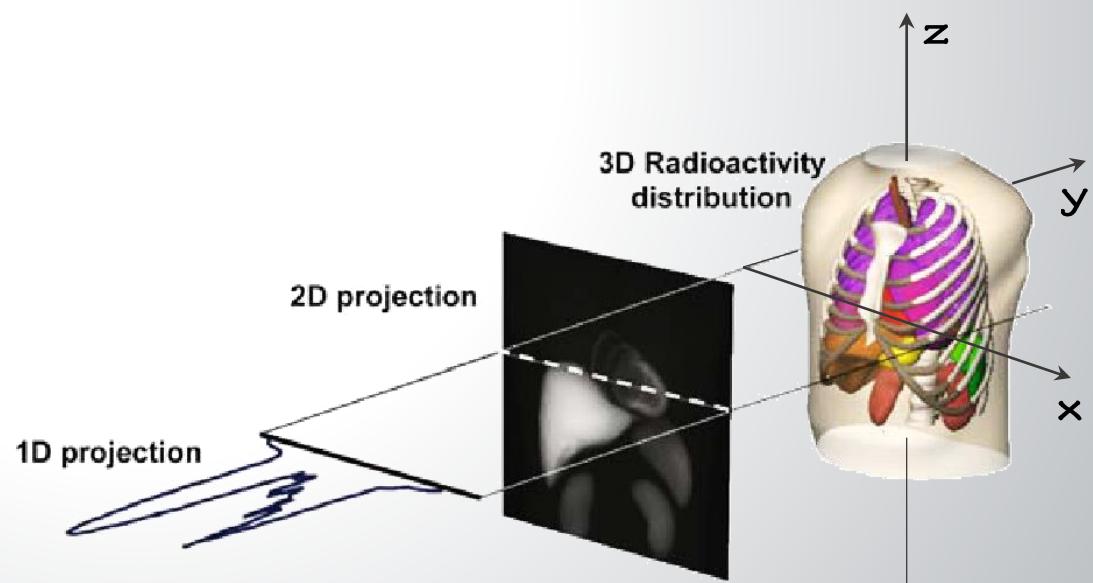
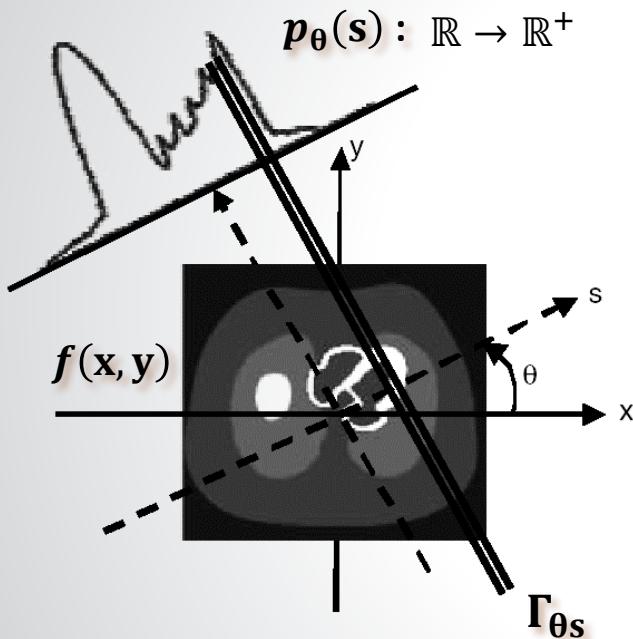
# Reconstruction

## ■ Modèle analytique



# Reconstruction

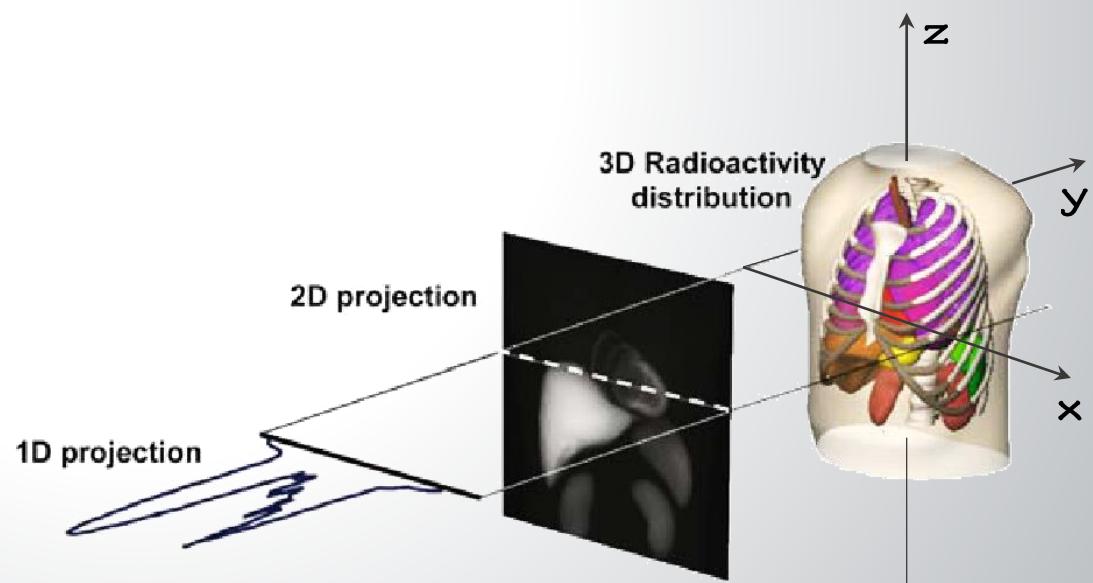
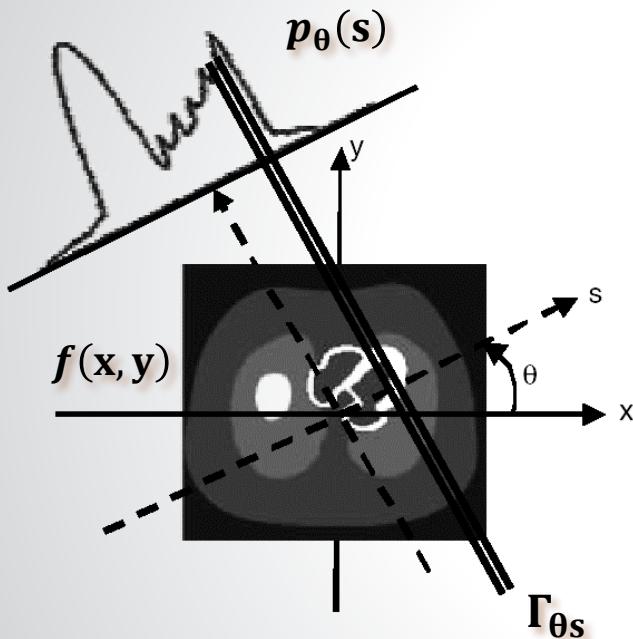
## ■ Modèle analytique



# Reconstruction

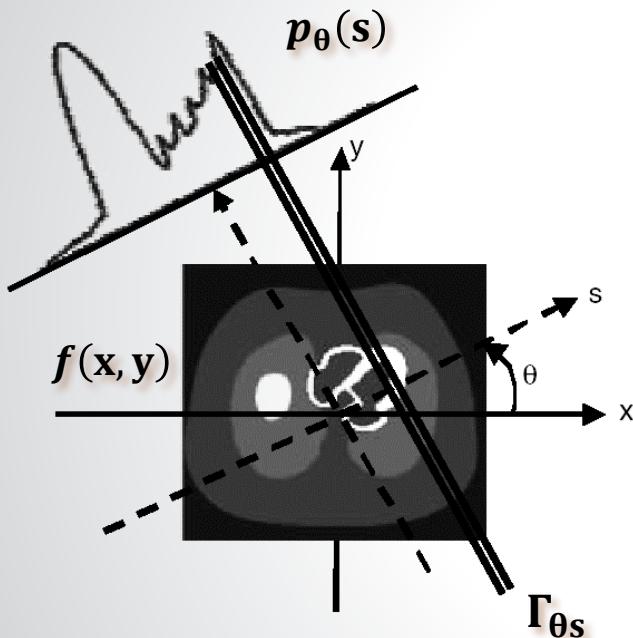
## ■ Modèle analytique

$$p_{\theta}(s) = \int_{\Gamma_{\theta s}} f(x, y)$$

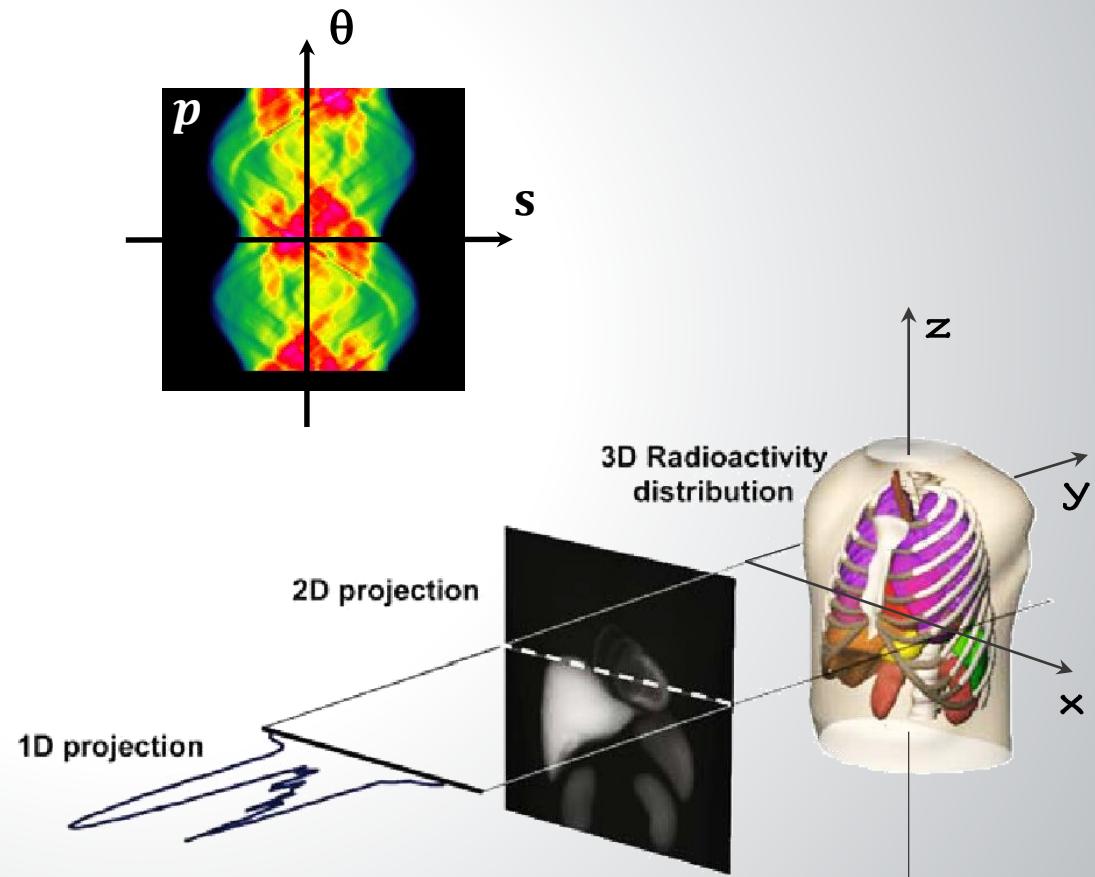


# Reconstruction

## ■ Modèle analytique



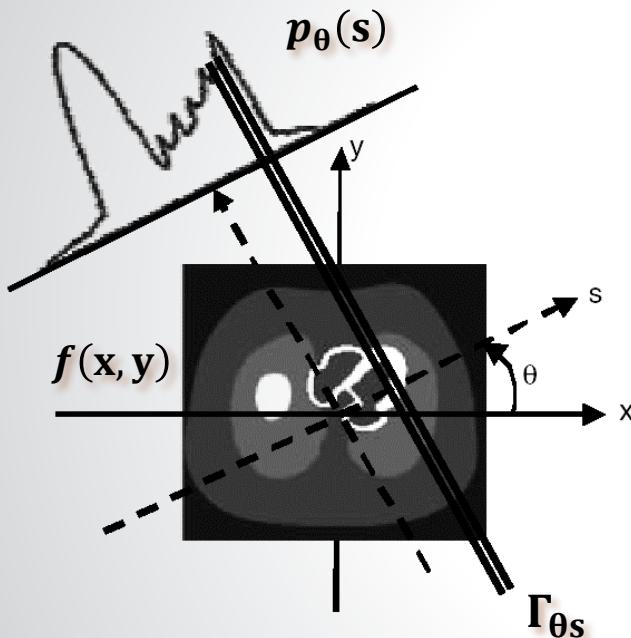
$$p_\theta(s) = \int_{\Gamma_{\theta s}} f(x, y)$$



# Reconstruction

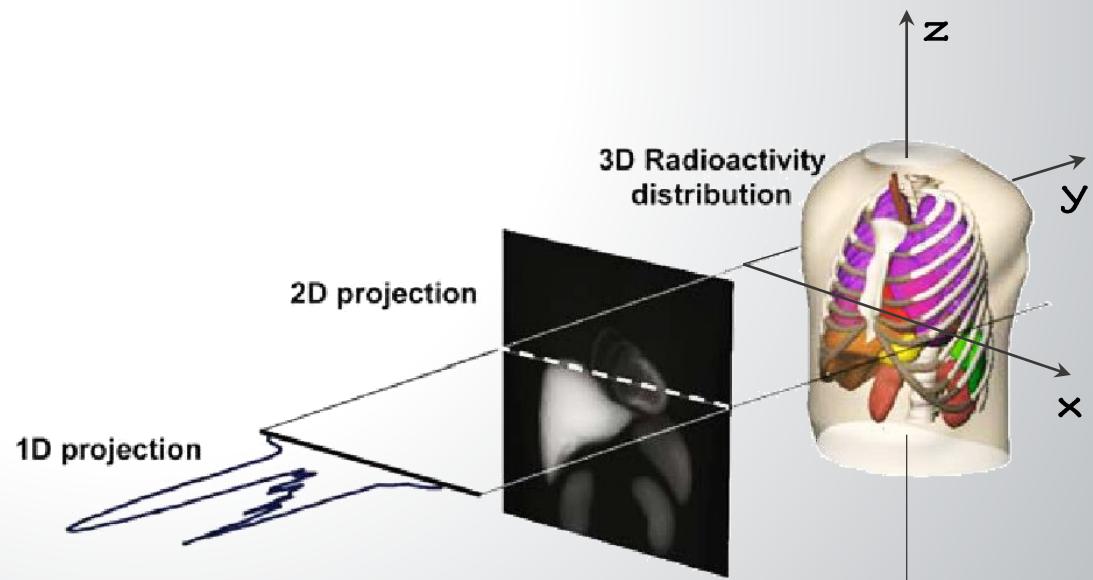
## ■ Modèle analytique

$$p_\theta(s) = \int_{\Gamma_{\theta s}} f(x, y)$$



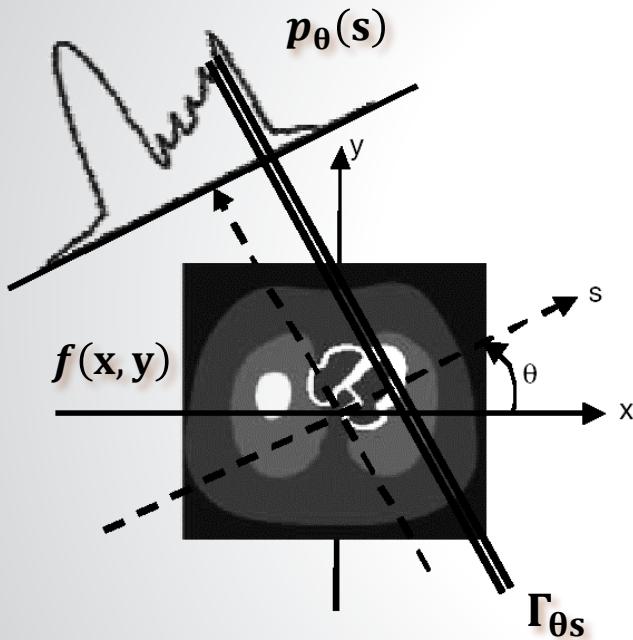
Projection (Radon):  $p = R f$

Rétro-projection:  $R^*$



# Reconstruction

## ■ Modèle analytique



### Projection

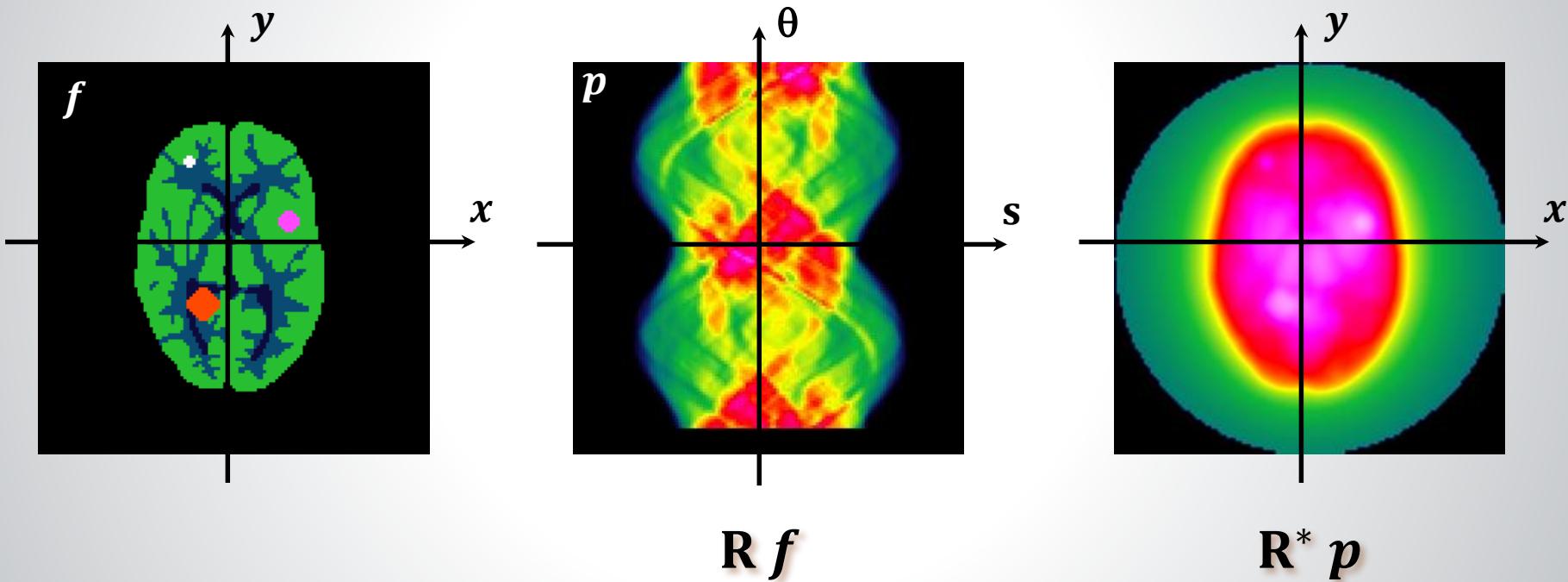
$$Rf_\theta(s) = \int_{\mathbb{R}} f(s \cos \theta - t \sin \theta, s \sin \theta + t \cos \theta) dt$$

### Rétro-projection

$$R^*p(x, y) = \int_0^\pi p_\theta(x \cos \theta + y \sin \theta) d\theta$$

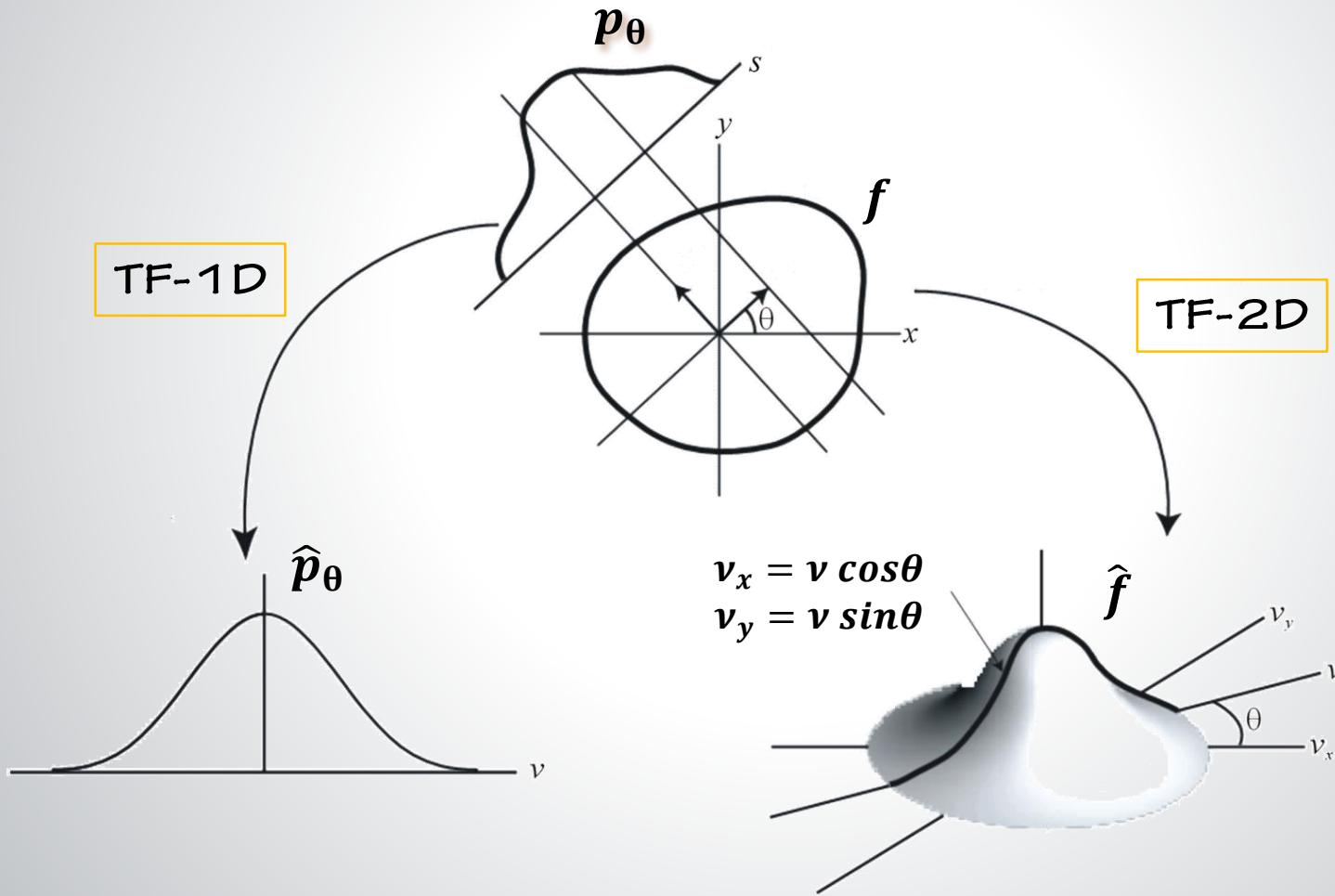
# Reconstruction

## ■ Modèle analytique



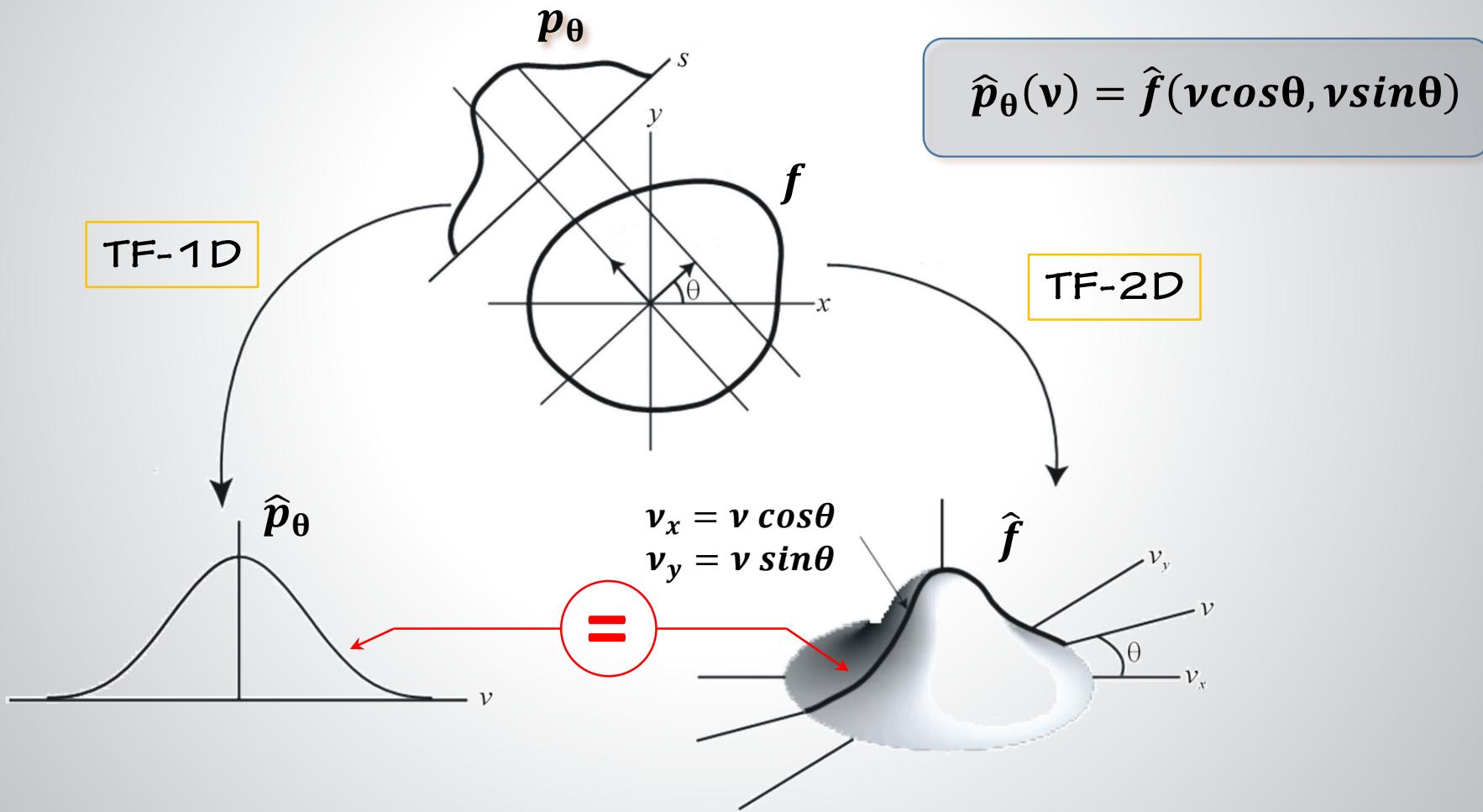
# Reconstruction

## ■ Modèle analytique — Synthèse de Fourier



# Reconstruction

## ■ Modèle analytique — Synthèse de Fourier



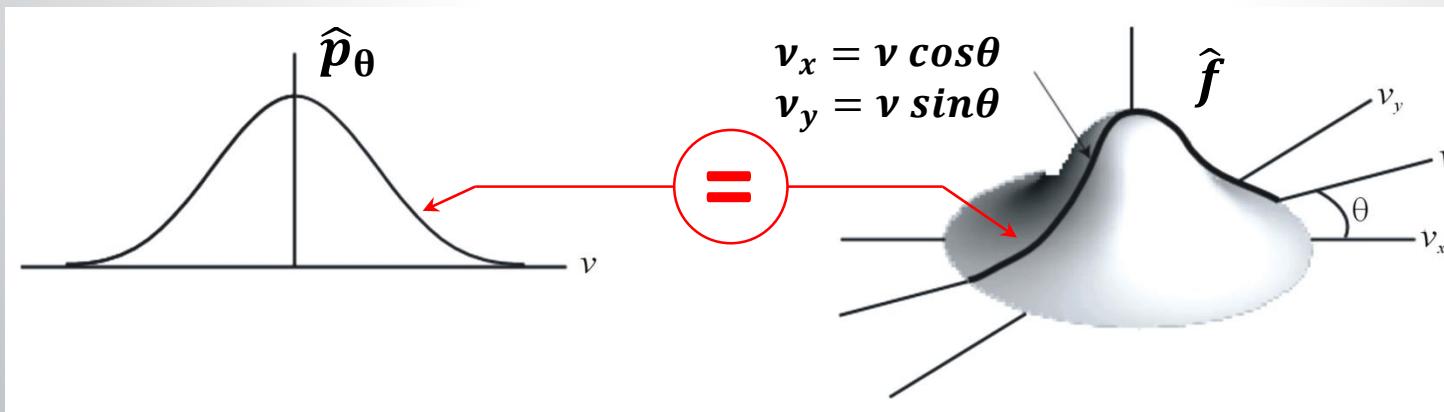
# Reconstruction

## ■ Modèle analytique — Synthèse de Fourier

$$\hat{p}_\theta(v) = \int_{\mathbb{R}} p_\theta(s) e^{-ivs} ds = \iint_{\mathbb{R}^2} f(s \cos \theta - t \sin \theta, s \sin \theta + t \cos \theta) e^{-ivs} ds dt$$

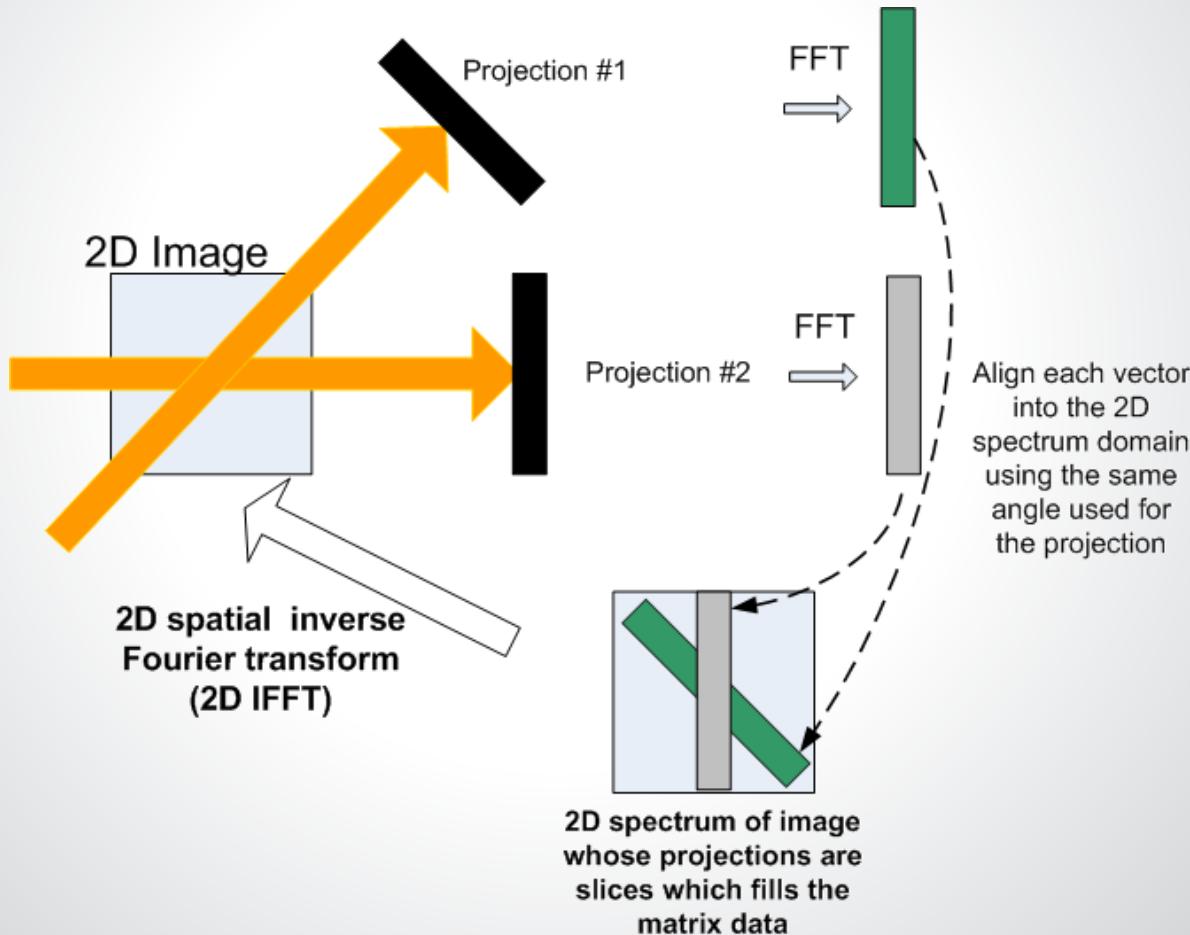
$$\begin{cases} x = s \cos \theta - t \sin \theta \\ y = s \sin \theta + t \cos \theta \end{cases} \quad \begin{cases} s = x \cos \theta + y \sin \theta \\ t = x \sin \theta - y \cos \theta \end{cases}$$

$$= \iint_{\mathbb{R}^2} f(x, y) e^{-iv(x \cos \theta + y \sin \theta)} dx dy = \hat{f}(v \cos \theta, v \sin \theta)$$



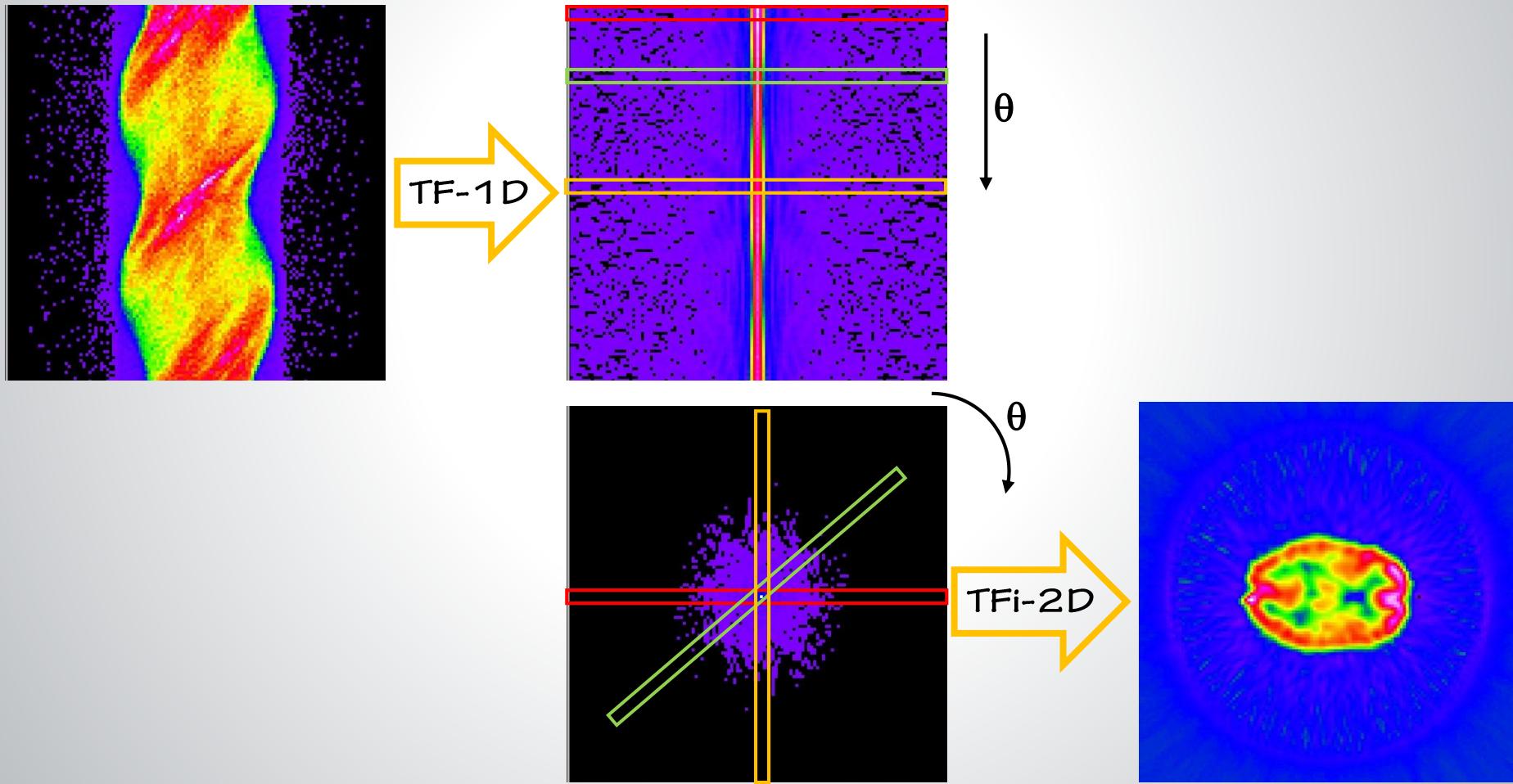
# Reconstruction

## ■ Modèle analytique — Synthèse de Fourier



# Reconstruction

## ■ Modèle analytique — Synthèse de Fourier



# Reconstruction

## ■ Modèle analytique — Rétro-projection filtrée

$$f = \iint_{\mathbb{R}^2} \hat{f} e^{i(x\nu_x + y\nu_y)} d\nu_x d\nu_y$$
$$\nu_x = \nu \cos\theta$$
$$\nu_y = \nu \sin\theta$$

# Reconstruction

## ■ Modèle analytique — Rétro-projection filtrée

$$f = \iint_{\mathbb{R}^2} \hat{f} e^{i(x\nu_x + y\nu_y)} d\nu_x d\nu_y$$
$$\begin{aligned}\nu_x &= \nu \cos\theta \\ \nu_y &= \nu \sin\theta\end{aligned}$$

$$f = \int d\theta \int \hat{f} e^{i\nu(x\cos\theta + y\sin\theta)} |\nu| d\nu$$

# Reconstruction

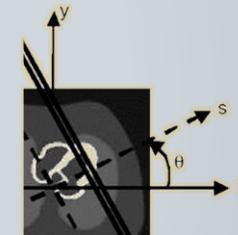
## ■ Modèle analytique — Rétro-projection filtrée

$$f = \iint_{\mathbb{R}^2} \hat{f} e^{i(x\nu_x + y\nu_y)} d\nu_x d\nu_y$$

$$\nu_x = \nu \cos\theta$$

$$\nu_y = \nu \sin\theta$$

$$f = \int d\theta \int \hat{f} e^{iv(x\cos\theta + y\sin\theta)} |v| dv$$



# Reconstruction

## ■ Modèle analytique — Rétro-projection filtrée

$$f = \iint_{\mathbb{R}^2} \hat{f} e^{i(x\nu_x + y\nu_y)} d\nu_x d\nu_y$$
$$\nu_x = v \cos\theta$$
$$\nu_y = v \sin\theta$$

$$f = \int d\theta \int \boxed{\hat{f}} e^{iv(x\cos\theta + y\sin\theta)} |v| dv$$

$\hat{f}(v\cos\theta, v\sin\theta) = \hat{p}_\theta(v)$

# Reconstruction

## ■ Modèle analytique — Rétro-projection filtrée

$$f = \iint_{\mathbb{R}^2} \hat{f} e^{i(x\nu_x + y\nu_y)} d\nu_x d\nu_y$$

$$\nu_x = \nu \cos\theta$$

$$\nu_y = \nu \sin\theta$$

$$f = \int d\theta \int \boxed{\hat{f}} e^{i\nu(x\cos\theta + y\sin\theta)} |\nu| d\nu$$

$\hat{f}(\nu\cos\theta, \nu\sin\theta) = \hat{p}_\theta(\nu)$

$$f = \int d\theta \int d\nu e^{is\nu} |\nu| \hat{p}$$

# Reconstruction

## ■ Modèle analytique — Rétro-projection filtrée

$$f = \iint_{\mathbb{R}^2} \hat{f} e^{i(x\nu_x + y\nu_y)} d\nu_x d\nu_y$$

$$\nu_x = \nu \cos\theta$$

$$\nu_y = \nu \sin\theta$$

$$f = \int d\theta \int \boxed{\hat{f}} e^{iv(x\cos\theta + y\sin\theta)} |\nu| d\nu$$

$\hat{f}(v\cos\theta, v\sin\theta) = \hat{p}_\theta(v)$

$$f = \int d\theta \int d\nu e^{is\nu} \boxed{|\nu| \hat{p}}$$

$\widehat{H}\hat{p} = |\nu| \hat{p}$

# Reconstruction

## ■ Modèle analytique — Rétro-projection filtrée

$$f = \iint_{\mathbb{R}^2} \hat{f} e^{i(x\nu_x + y\nu_y)} d\nu_x d\nu_y$$

$$\nu_x = \nu \cos\theta$$

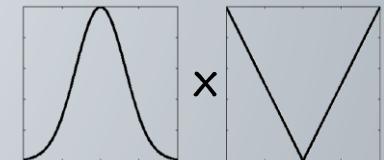
$$\nu_y = \nu \sin\theta$$

$$f = \int d\theta \int \boxed{\hat{f}} e^{iv(x\cos\theta + y\sin\theta)} |v| dv$$

$$\hat{f}(v\cos\theta, v\sin\theta) = \hat{p}_\theta(v)$$

$$f = \int d\theta \int dv e^{isv} \circled{|\nu| \hat{p}}$$

$$\widehat{H}p = |\nu| \hat{p}$$



Filtre rampe

# Reconstruction

## ■ Modèle analytique — Rétro-projection filtrée

$$f = \iint_{\mathbb{R}^2} \hat{f} e^{i(x\nu_x + y\nu_y)} d\nu_x d\nu_y$$

$$\nu_x = \nu \cos\theta$$

$$\nu_y = \nu \sin\theta$$

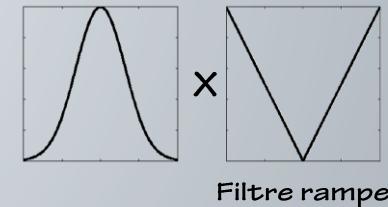
$$f = \int d\theta \int \boxed{\hat{f}} e^{iv(x\cos\theta + y\sin\theta)} |v| dv$$

$$\hat{f}(v\cos\theta, v\sin\theta) = \hat{p}_\theta(v)$$

$$f = \int d\theta \int dv e^{isv} |v| \hat{p}$$

$$\widehat{H}p = |v| \hat{p}$$

TF inv - 1D



# Reconstruction

## ■ Modèle analytique — Rétro-projection filtrée

$$f = \iint_{\mathbb{R}^2} \hat{f} e^{i(x\nu_x + y\nu_y)} d\nu_x d\nu_y$$

$$\nu_x = \nu \cos\theta$$

$$\nu_y = \nu \sin\theta$$

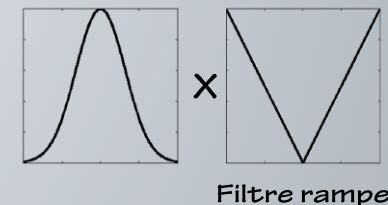
$$f = \int d\theta \int \boxed{\hat{f}} e^{iv(x\cos\theta + y\sin\theta)} |v| dv$$

$$\hat{f}(v\cos\theta, v\sin\theta) = \hat{p}_\theta(v)$$

$$f = \int d\theta \int dv e^{isv} |v| \hat{p}$$

$$\widehat{H}\hat{p} = |v| \hat{p}$$

TF inv - 1D  
Rétro-projection



# Reconstruction

## ■ Modèle analytique — Rétro-projection filtrée

$$f = \iint_{\mathbb{R}^2} \hat{f} e^{i(x\nu_x + y\nu_y)} d\nu_x d\nu_y$$

$$\nu_x = \nu \cos\theta$$

$$\nu_y = \nu \sin\theta$$

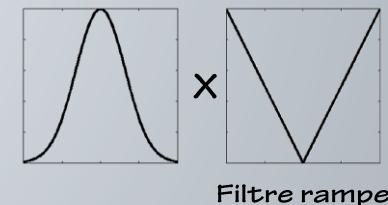
$$f = \int d\theta \int \boxed{\hat{f}} e^{iv(x\cos\theta + y\sin\theta)} |v| dv$$

$$\hat{f}(v\cos\theta, v\sin\theta) = \hat{p}_\theta(v)$$

$$f = \boxed{\int d\theta} \boxed{\int dv e^{isv} |v| \hat{p}}$$

$$\widehat{H}p = |v| \hat{p}$$

TF inv - 1D  
Rétro-projection



$$f = \mathbf{R}^* \mathbf{H}p$$

# Reconstruction

## ■ Modèle analytique — Rétro-projection filtrée

$$\mathbf{H}p = \mathbf{T}\mathbf{F}^{-1}(\hat{\mathbf{h}}\hat{p})$$

$$\hat{\mathbf{h}}(\nu) = |\nu|$$

$$\mathbf{H}p = h * p$$

# Reconstruction

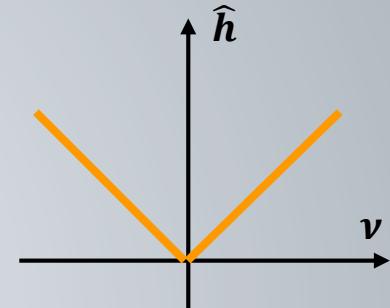
## ■ Modèle analytique — Rétro-projection filtrée

$$\mathbf{H}p = \mathbf{T}\mathbf{F}^{-1}(\hat{h} \hat{p})$$

$$\hat{h}(\nu) = |\nu|$$

$$\mathbf{H}p = h * p$$

$$h(s) = \int_{\mathbb{R}} \hat{h}(\nu) e^{i\nu s} d\nu$$



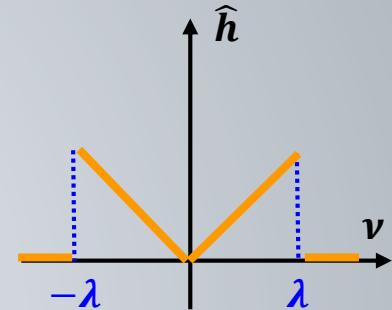
# Reconstruction

## ■ Modèle analytique — Rétro-projection filtrée

$$Hp = \text{TF}^{-1}(\hat{h} \hat{p})$$

$$Hp = h * p$$

$$h(s) = \int_{-\lambda}^{\lambda} \hat{h}(\nu) e^{i\nu s} d\nu$$



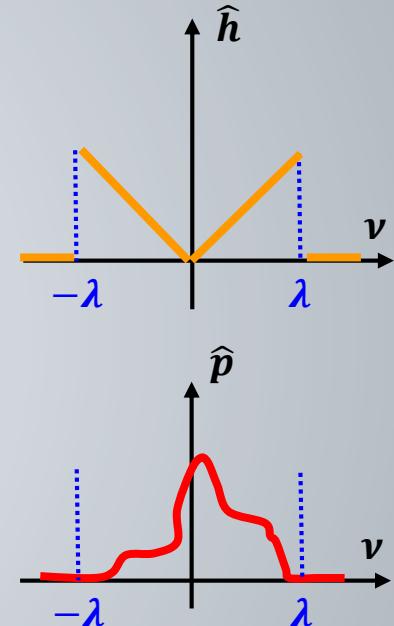
# Reconstruction

## ■ Modèle analytique — Rétro-projection filtrée

$$H\mathbf{p} = \text{TF}^{-1}(\hat{\mathbf{h}} \hat{\mathbf{p}})$$

$$H\mathbf{p} = \mathbf{h} * \mathbf{p}$$

$$\mathbf{h}(s) = \int_{-\lambda}^{\lambda} \hat{\mathbf{h}}(\nu) e^{i\nu s} d\nu$$



$$\begin{aligned}\lambda &\geq \nu_{max} \\ &= 2\pi F_{max} = \pi\end{aligned}$$

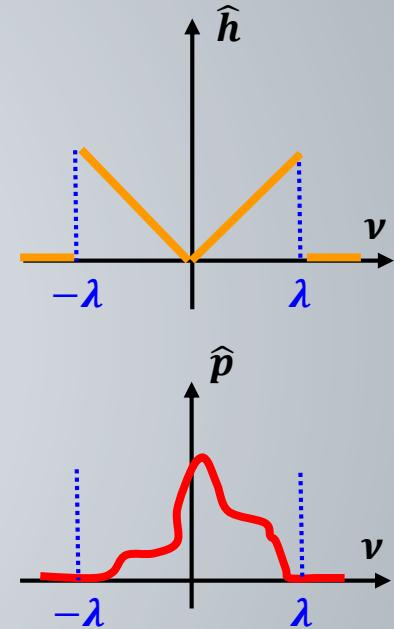
# Reconstruction

## ■ Modèle analytique — Rétro-projection filtrée

$$Hp = \text{TF}^{-1}(\hat{h} \hat{p})$$

$$Hp = h * p$$

$$\begin{aligned} h(s) &= \int_{-\lambda}^{\lambda} \hat{h}(\nu) e^{i\nu s} d\nu \\ &= - \int_{-\pi}^0 \nu e^{i\nu s} d\nu + \int_0^\pi \nu e^{i\nu s} d\nu \\ &= \frac{2\pi}{s} \sin(\pi s) + \frac{2}{s^2} (\cos(\pi s) - 1) \end{aligned}$$



$$\begin{aligned} \lambda &\geq \nu_{max} \\ &= 2\pi F_{max} = \pi \end{aligned}$$

# Reconstruction

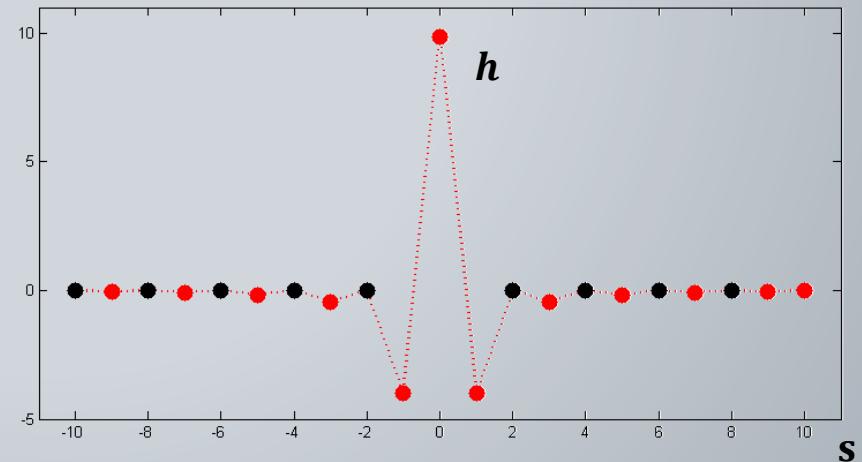
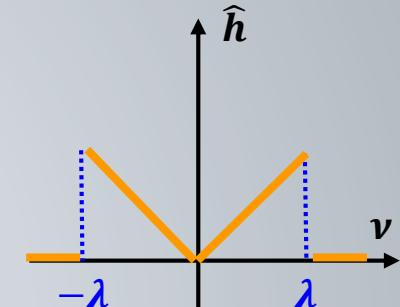
## ■ Modèle analytique — Rétro-projection filtrée

$$H\mathbf{p} = \text{TF}^{-1}(\hat{\mathbf{h}} \hat{\mathbf{p}})$$

$$H\mathbf{p} = h * p$$

$$h(s) = \int_{-\lambda}^{\lambda} \hat{h}(\nu) e^{i\nu s} d\nu$$

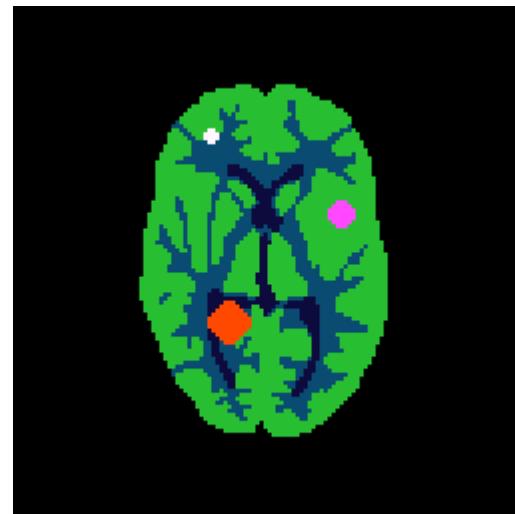
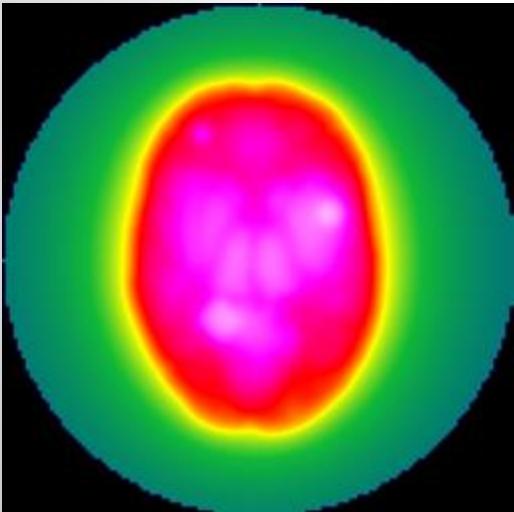
$$= \begin{cases} \pi^2 & \text{en } 0 \\ 0 & \text{pour } s \text{ pair} \\ -\frac{4}{s^2} & \text{pour } s \text{ impair} \end{cases}$$



# Reconstruction

- Modèle analytique — Rétro-projection filtrée

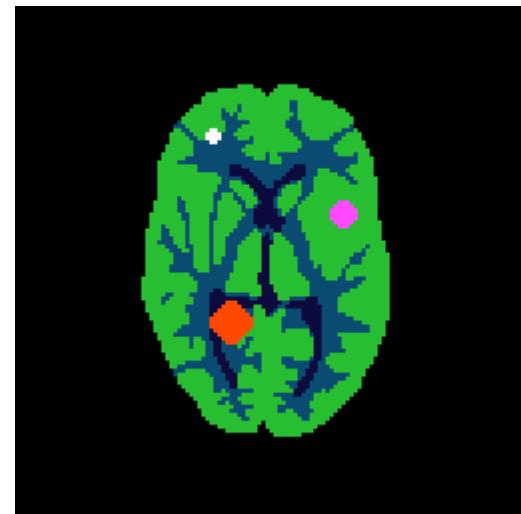
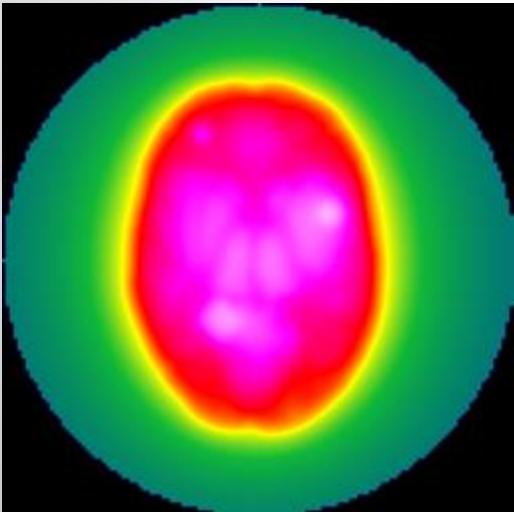
$$f = \mathbf{R}^* p$$



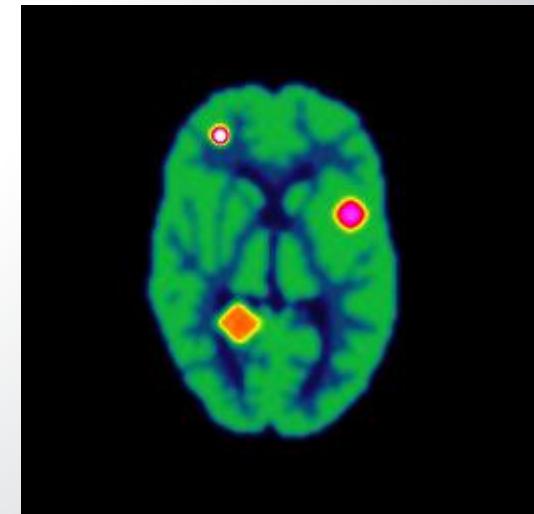
# Reconstruction

- Modèle analytique — Rétro-projection filtrée

$$f = \mathbf{R}^* p$$



$$f = \mathbf{R}^* \mathbf{H}p$$

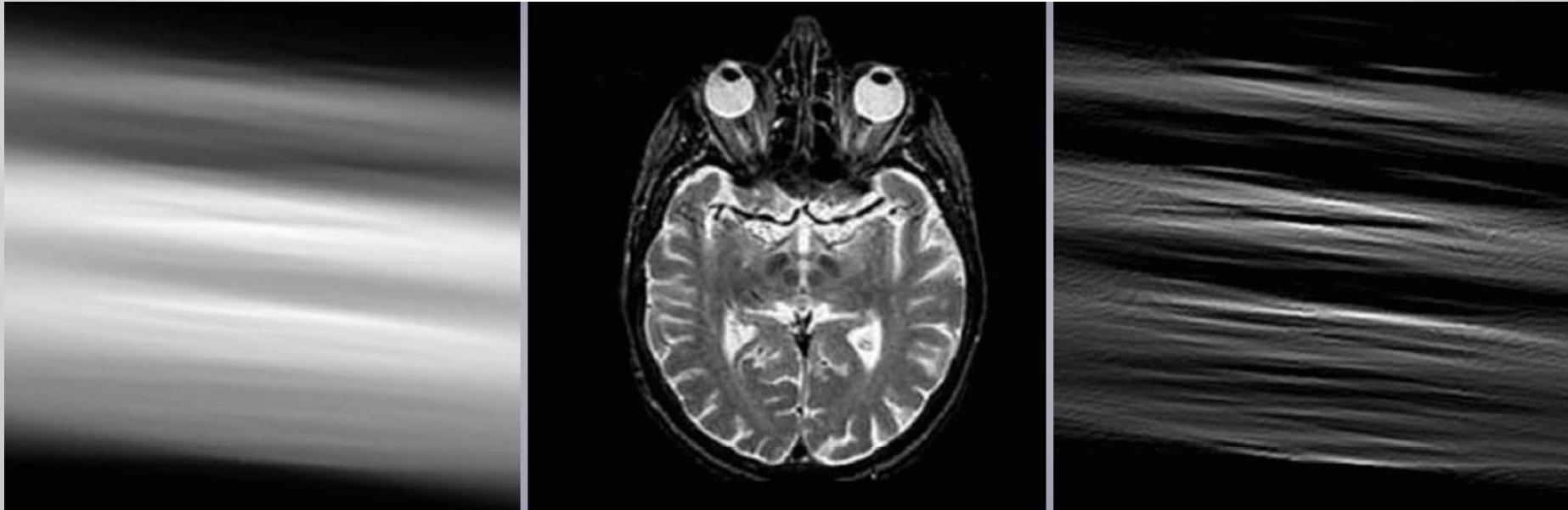


# Reconstruction

- Modèle analytique — Rétro-projection filtrée

$$f = \mathbf{R}^* p$$

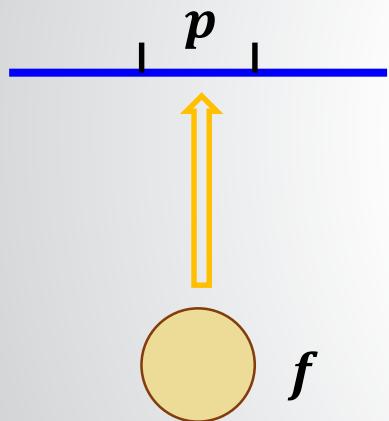
$$f = \mathbf{R}^* \mathbf{H}p$$



# Reconstruction

## ■ Modèle analytique — Limites

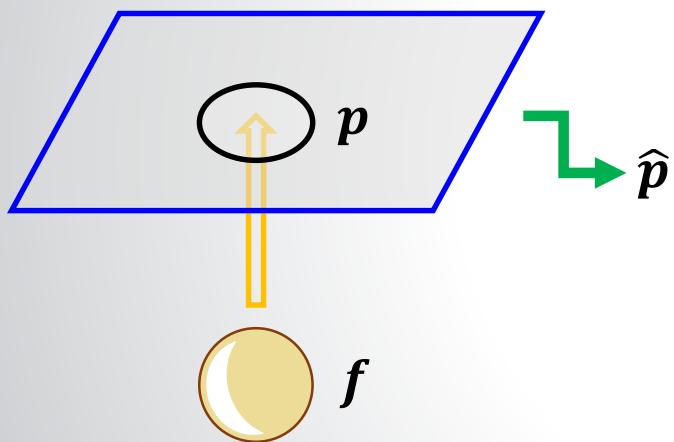
Troncature des données



# Reconstruction

## ■ Modèle analytique — Limites

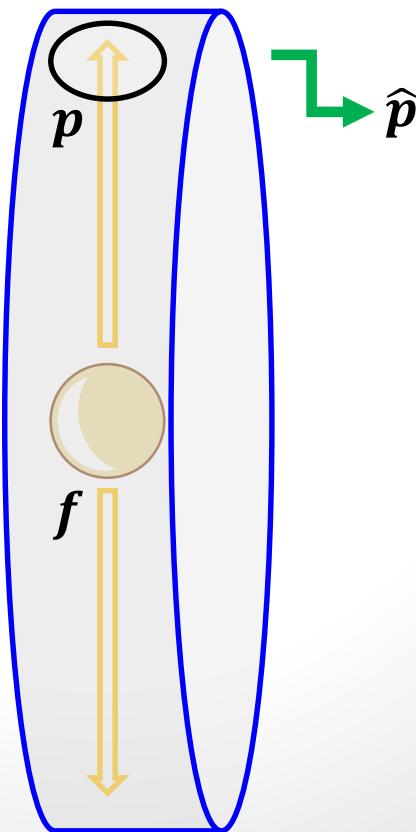
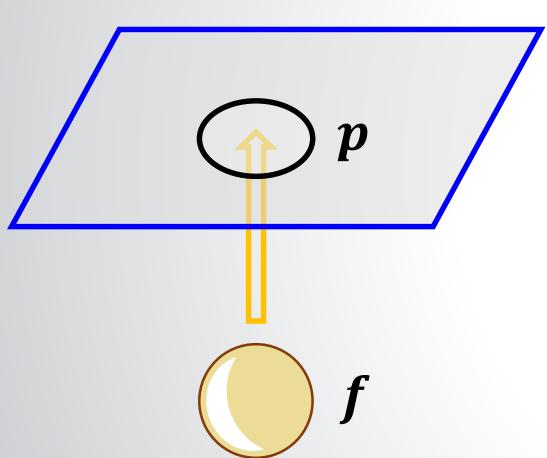
Troncature des données



# Reconstruction

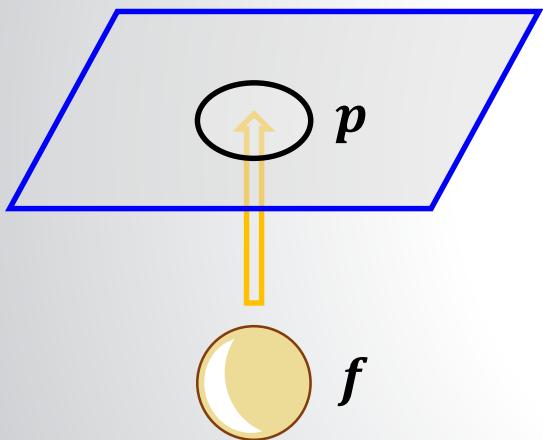
## ■ Modèle analytique — Limites

Troncature des données

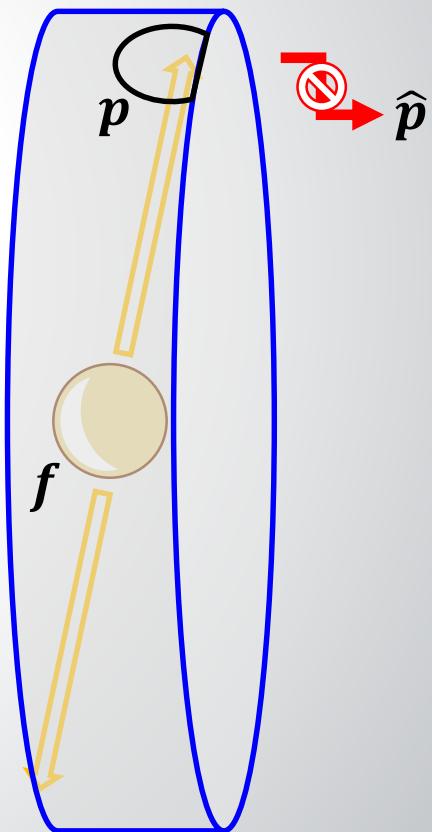
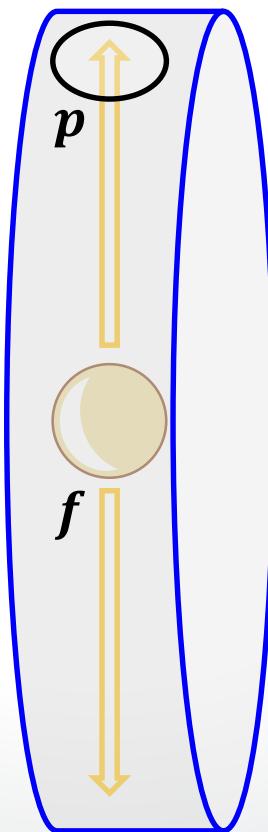


# Reconstruction

## ■ Modèle analytique — Limites



## Troncature des données

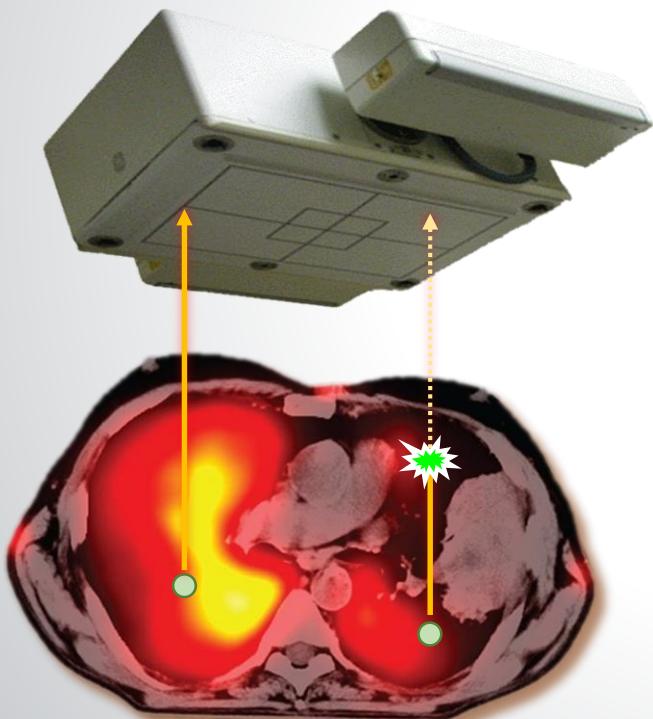


# Reconstruction

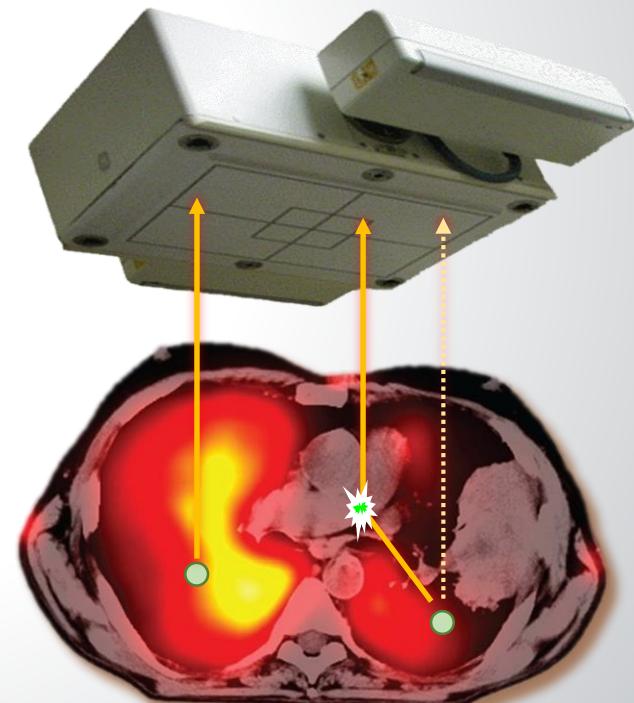
## ■ Modèle analytique — Limites

Interactions  $\gamma$  - matière

Absorption

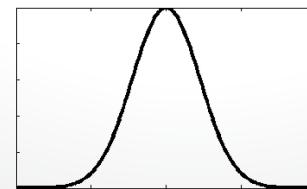
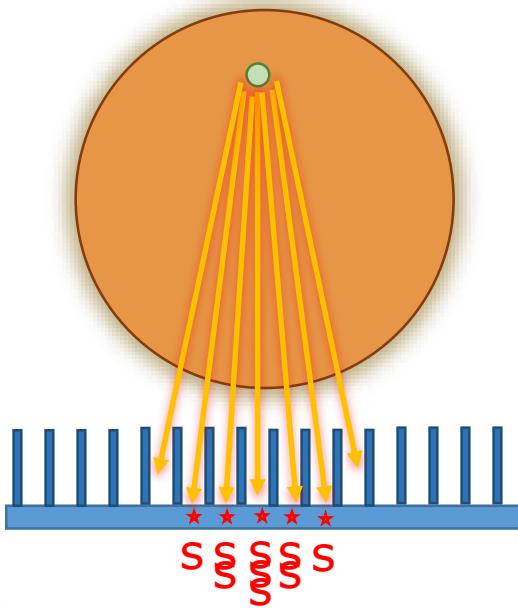
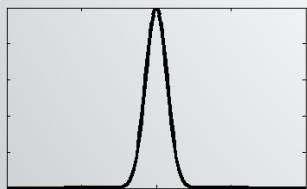
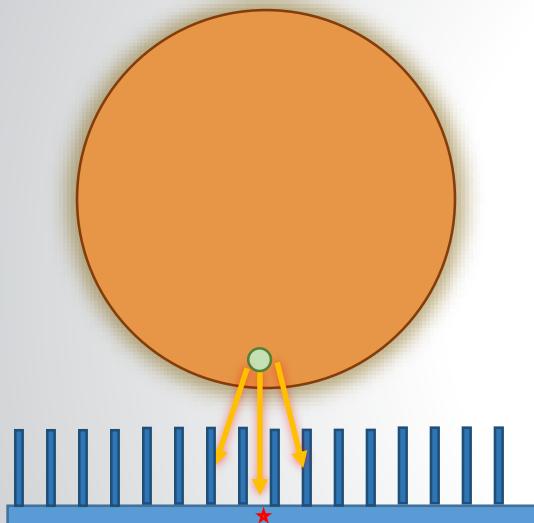


Diffusion

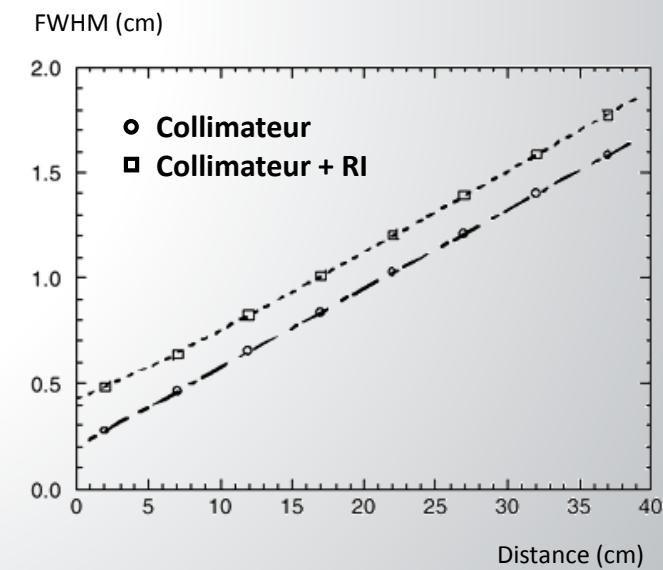


# Reconstruction

## ■ Modèle analytique — Limites



## Réponse du détecteur



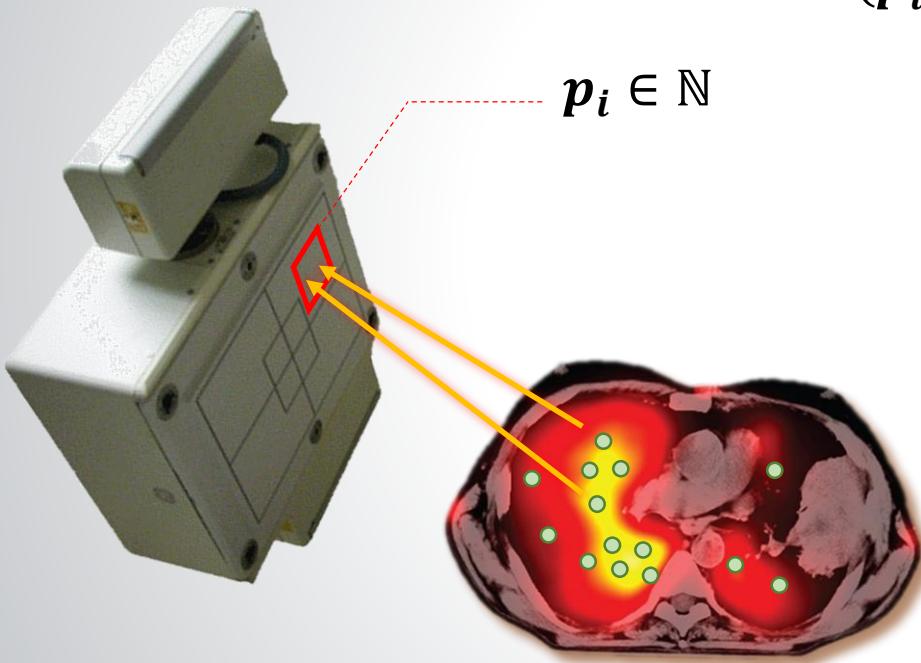
# Reconstruction

## ■ Modèle analytique — Limites

## Bruit statistique

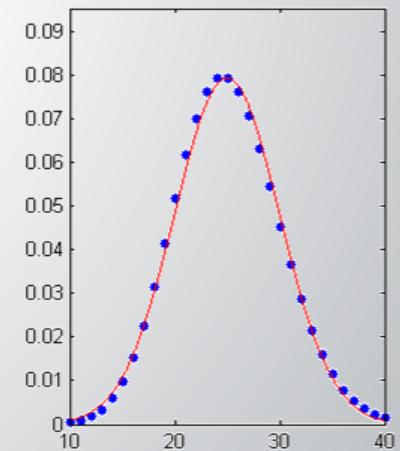
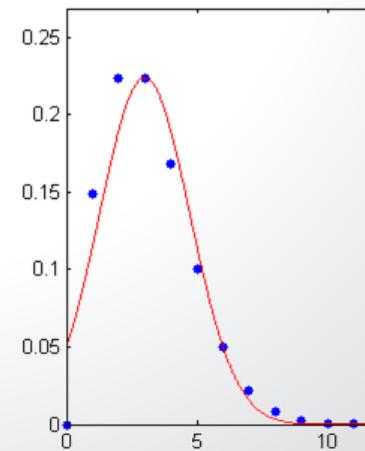
$$E(\mathbf{p}_i) = \kappa \int_{\Gamma_i} f$$

$$\mathbf{p}_i \in \mathbb{N}$$



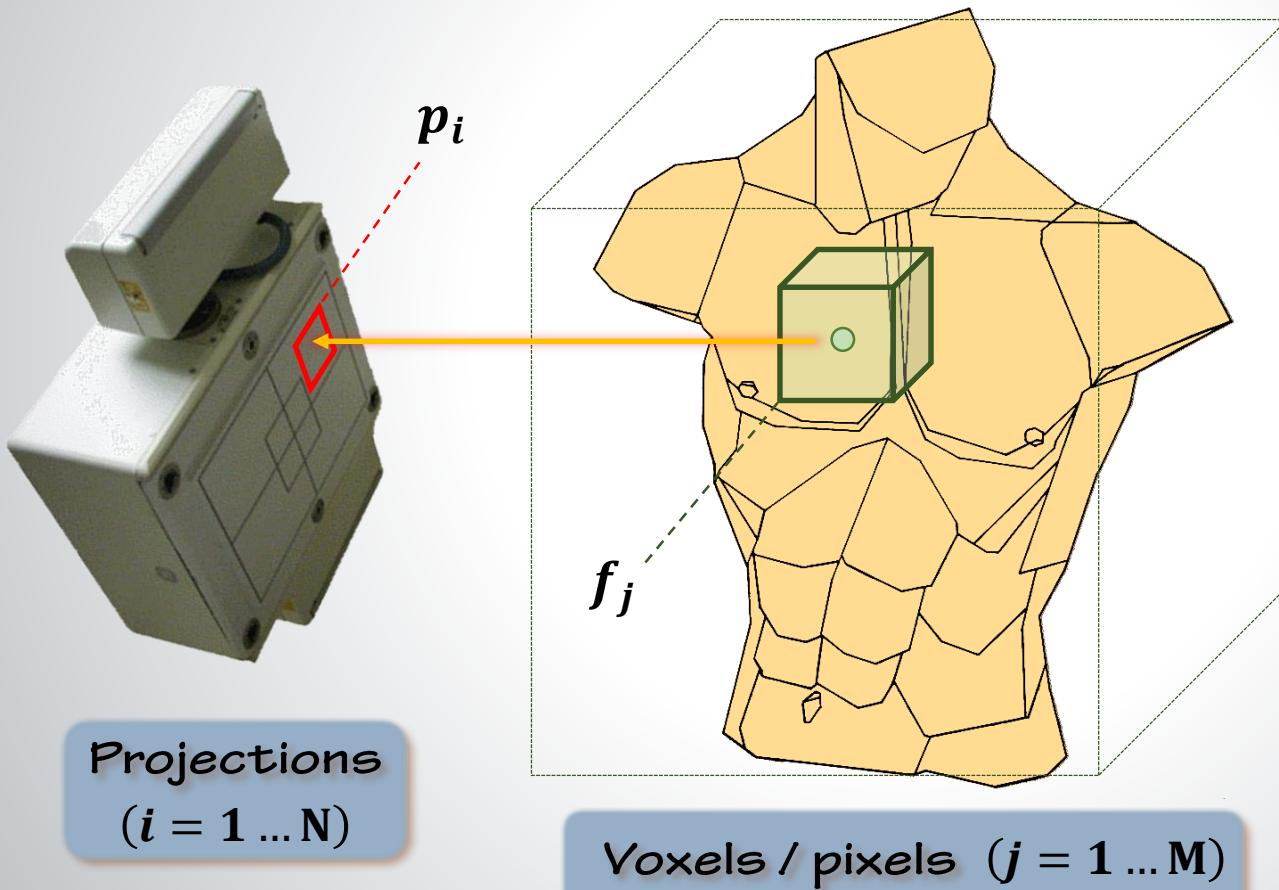
$$Var(\mathbf{p}_i) = E(\mathbf{p}_i)$$

$$SNR = \frac{E(\mathbf{p}_i)}{\sigma(\mathbf{p}_i)} \approx \sqrt{p_i}$$



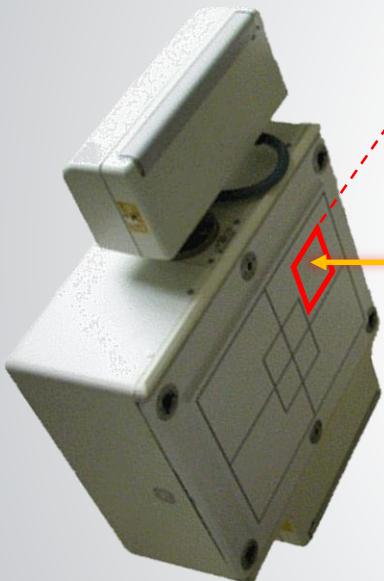
# Reconstruction

## ■ Modèle algébrique

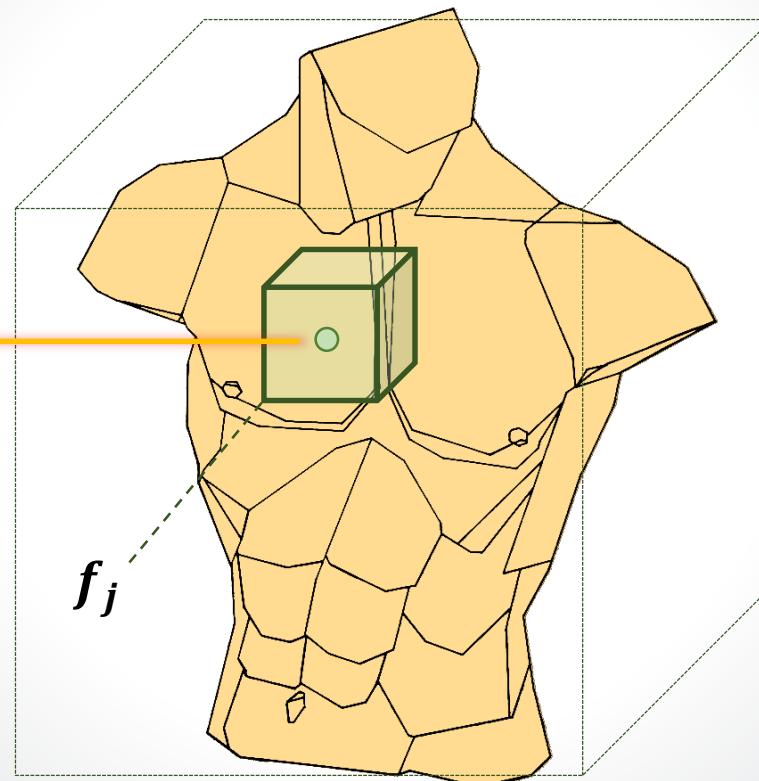


# Reconstruction

## ■ Modèle algébrique



Projections  
( $i = 1 \dots N$ )



Voxels / pixels ( $j = 1 \dots M$ )

Matrice système

$$\mathbf{R} \in \mathbb{R}^{N \times M}$$

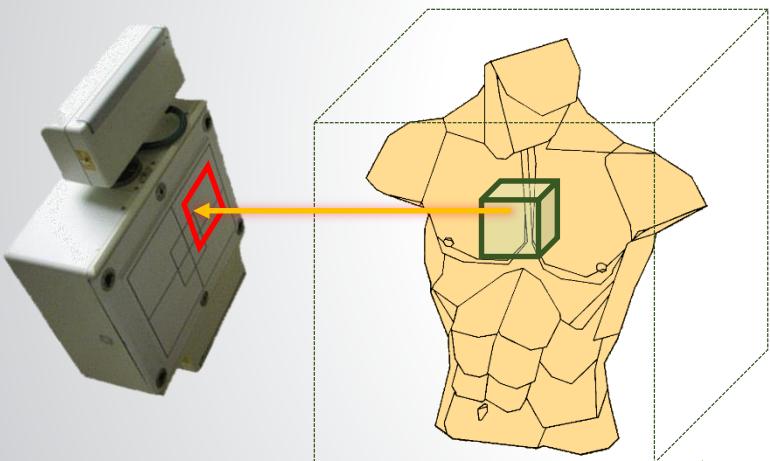
$$R_{ij} = \rho(j \rightarrow i)$$

- > Géométrie
- > Atténuation
- > Réponse du détecteur

# Reconstruction

## ■ Modèle algébrique

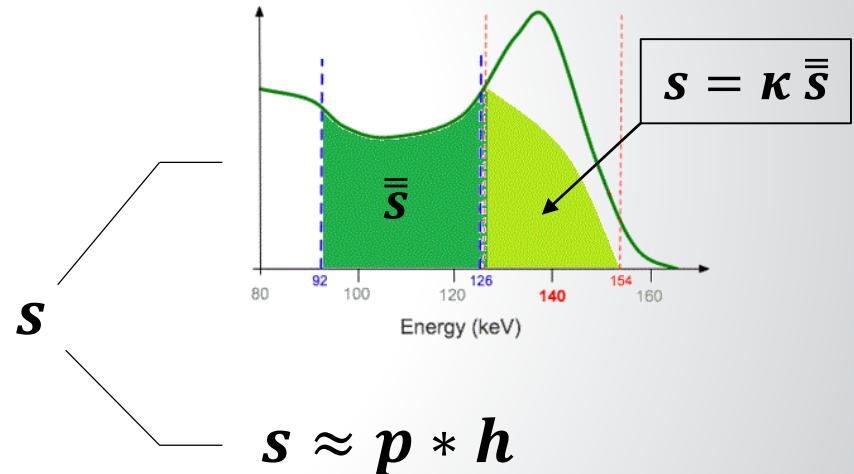
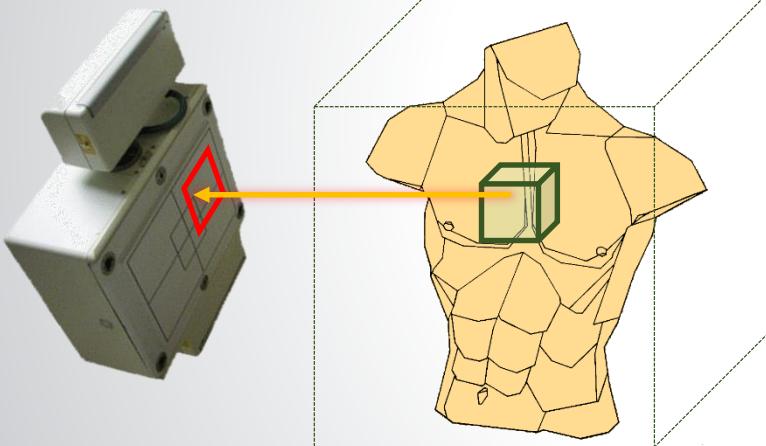
$$p = \mathbf{R}f + s + n$$



# Reconstruction

## ■ Modèle algébrique

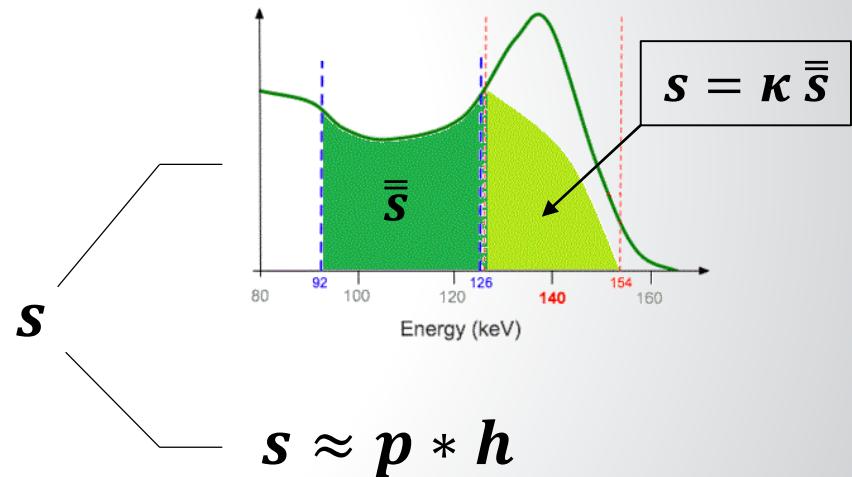
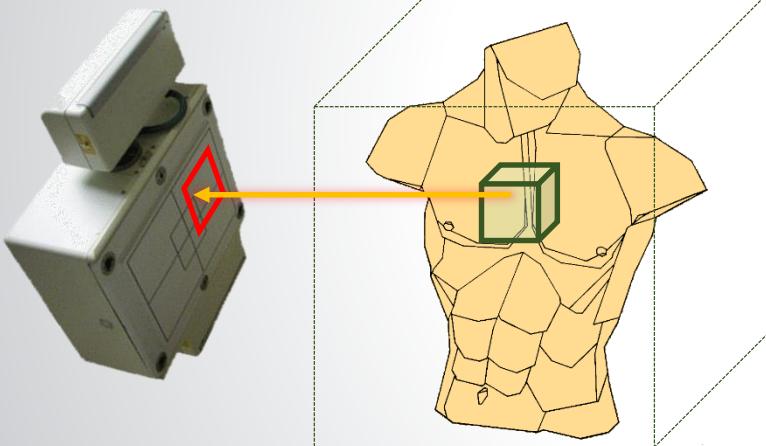
$$p = \mathbf{R}f + s + n$$



# Reconstruction

## ■ Modèle algébrique

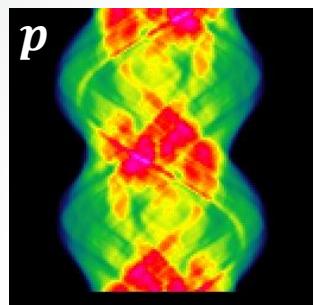
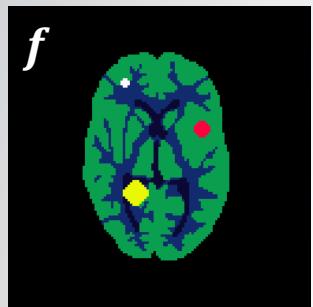
$$p = \mathbf{R}f + s + n$$



$$E(n) = 0 ; V(n) \approx p$$

# Reconstruction

## ■ Modèle algébrique

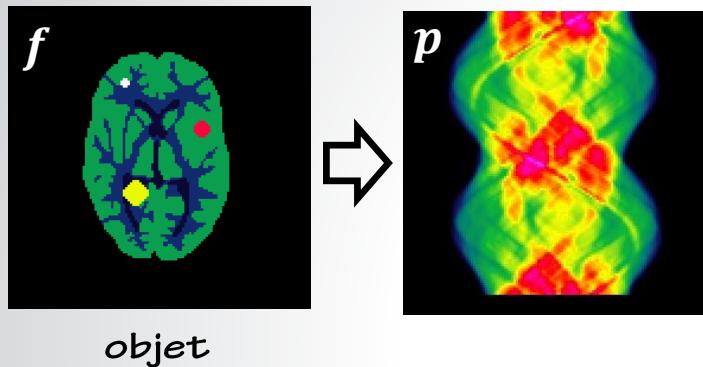


*objet*

$$p = \mathbf{R}f + n$$

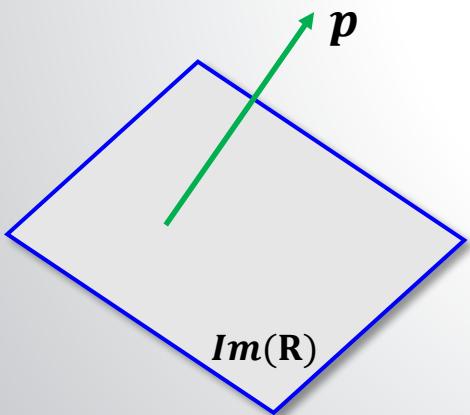
# Reconstruction

## ■ Modèle algébrique



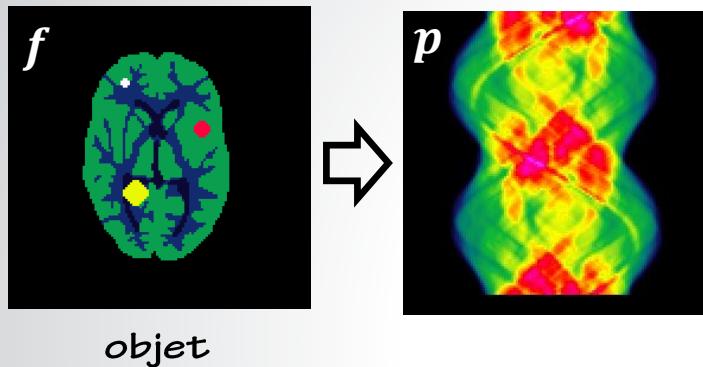
$$p = \mathbf{R}f + n$$

$$p \notin \text{Im}(\mathbf{R}) \quad \exists \bar{f} : \mathbf{R}\bar{f} = p$$



# Reconstruction

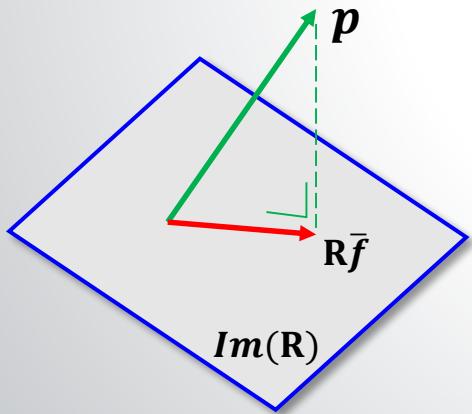
## ■ Modèle algébrique



$$p = \mathbf{R}f + n$$

$$p \notin \text{Im}(\mathbf{R}) \quad \exists \bar{f} : \mathbf{R}\bar{f} = p$$

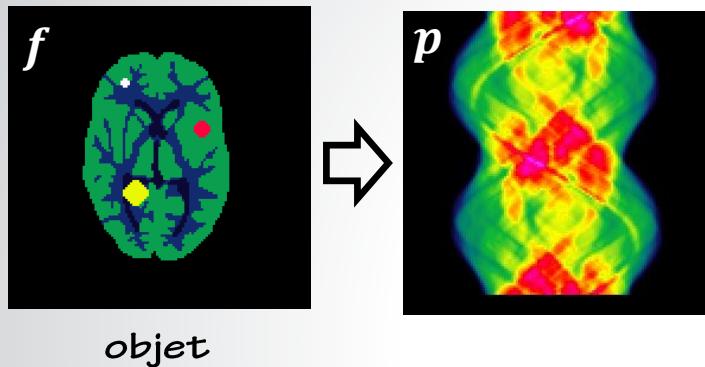
$$\bar{f} : \mathbf{R}\bar{f} = \mathbf{P}_{\text{Im}(\mathbf{R})}(p)$$



$$\bar{f} = \underset{f \in \Omega}{\operatorname{argmin}} \ \| \mathbf{R}f - p \|$$

# Reconstruction

## ■ Modèle algébrique

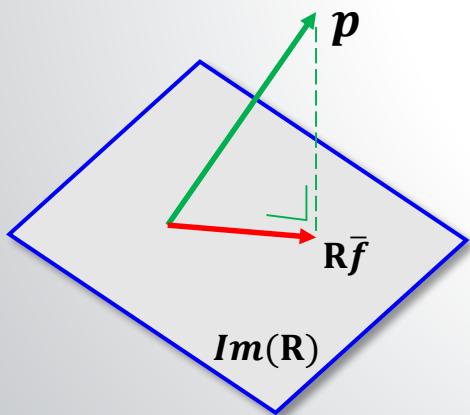


$$p = \mathbf{R}f + n$$

$$p \notin \text{Im}(\mathbf{R}) \quad \exists \bar{f} : \mathbf{R}\bar{f} = p$$

$$\bar{f} : \mathbf{R}\bar{f} = \mathbf{P}_{\text{Im}(\mathbf{R})}(p)$$

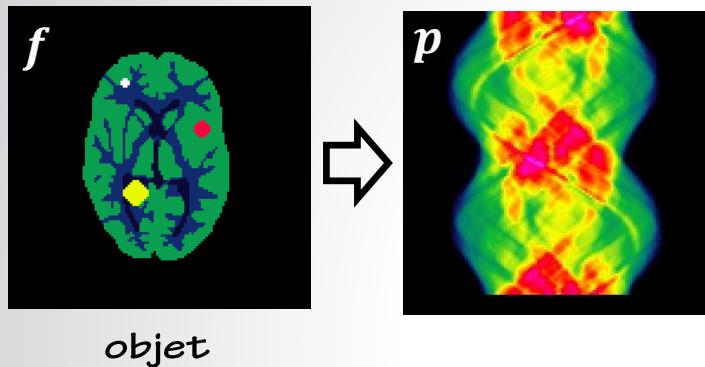
$$\forall w \in \text{Im}(R) : w^T \mathbf{R}\bar{f} = w^T p$$



$$\bar{f} = \underset{f \in \Omega}{\operatorname{argmin}} \ \| \mathbf{R}f - p \|$$

# Reconstruction

## ■ Modèle algébrique



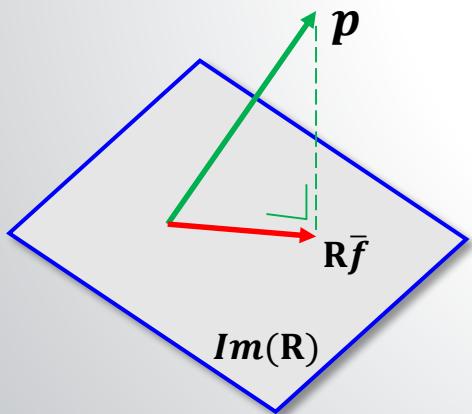
$$p = Rf + n$$

$$p \notin Im(R) \quad \exists \bar{f} : R\bar{f} = p$$

$$\bar{f} : R\bar{f} = P_{Im(R)}(p)$$

$$\forall w \in Im(R) : w^T R \bar{f} = w^T p$$

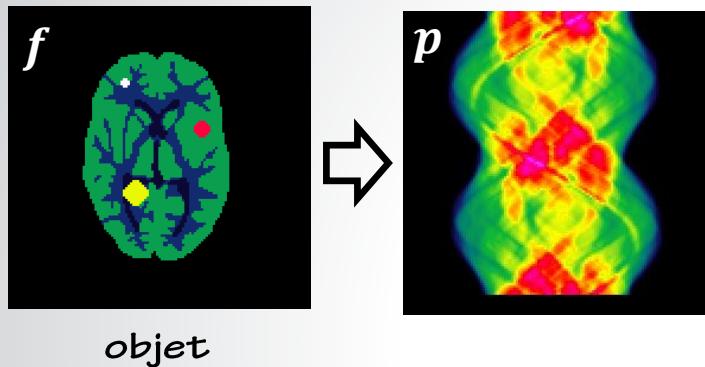
$$\forall g \in \Omega : (Rg)^T R \bar{f} = (Rg)^T p$$



$$\bar{f} = \underset{f \in \Omega}{argmin} \ \|Rf - p\|$$

# Reconstruction

## ■ Modèle algébrique



$$p = Rf + n$$

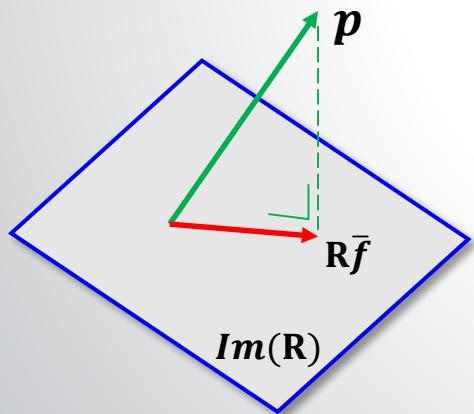
$$p \notin Im(R) \quad \exists \bar{f} : R\bar{f} = p$$

$$\bar{f} : R\bar{f} = P_{Im(R)}(p)$$

$$\forall w \in Im(R) : w^T R \bar{f} = w^T p$$

$$\forall g \in \Omega : (Rg)^T R \bar{f} = (Rg)^T p$$

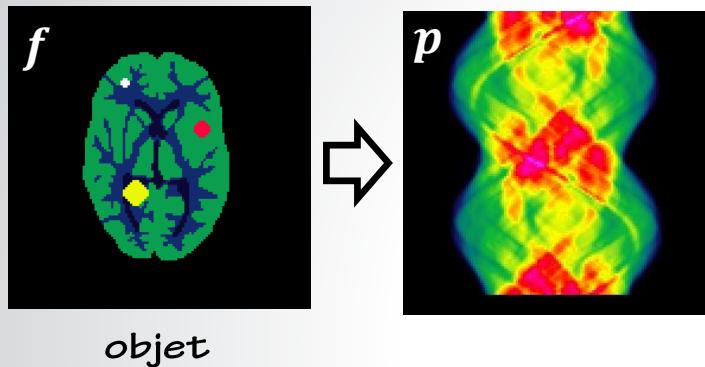
$$\forall g \in \Omega : g^T R^* R \bar{f} = g^T R^* p$$



$$\bar{f} = \underset{f \in \Omega}{argmin} \ \|Rf - p\|$$

# Reconstruction

## ■ Modèle algébrique



$$p = Rf + n$$

$$p \notin Im(R) \quad \exists \bar{f} : R\bar{f} = p$$

$$\bar{f} : R\bar{f} = P_{Im(R)}(p)$$

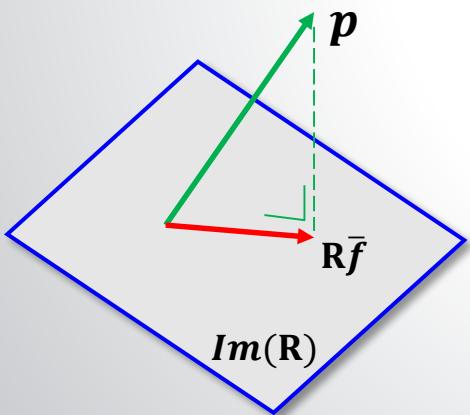
$$\forall w \in Im(R) : w^T R \bar{f} = w^T p$$

$$\forall g \in \Omega : (Rg)^T R \bar{f} = (Rg)^T p$$

$$\forall g \in \Omega : g^T R^* R \bar{f} = g^T R^* p$$

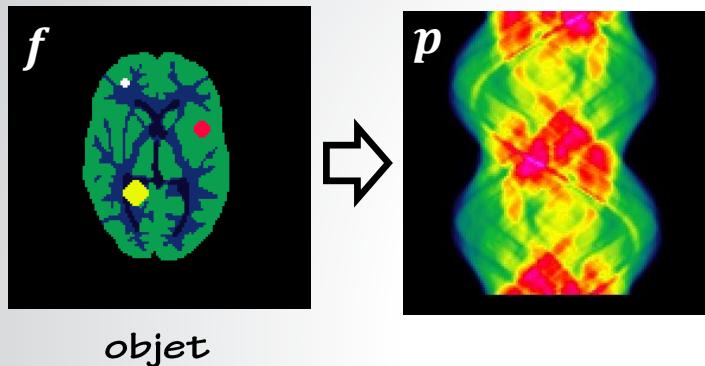
$$R^* R \bar{f} = R^* p$$

$$\bar{f} = \underset{f \in \Omega}{argmin} \ \|Rf - p\|$$



# Reconstruction

## ■ Modèle algébrique



$$p = Rf + n$$

$$p \notin Im(R) \quad \exists \bar{f} : R\bar{f} = p$$

$$\bar{f} : R\bar{f} = P_{Im(R)}(p)$$

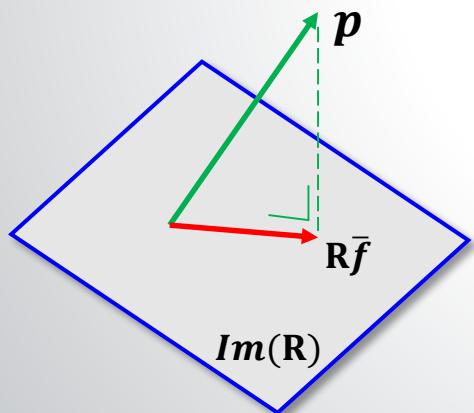
$$\forall w \in Im(R) : w^T R \bar{f} = w^T p$$

$$\forall g \in \Omega : (Rg)^T R \bar{f} = (Rg)^T p$$

$$\forall g \in \Omega : g^T R^* R \bar{f} = g^T R^* p$$

$$R^* R \bar{f} = R^* p$$

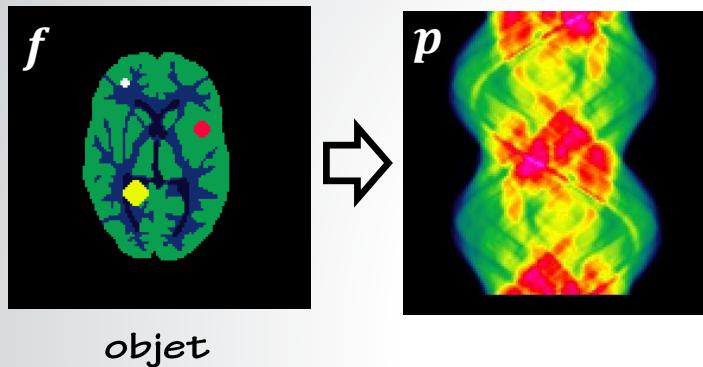
$$\bar{f} = (R^* R)^{-1} R^* p$$



$$\bar{f} = \underset{f \in \Omega}{argmin} \ \|Rf - p\|$$

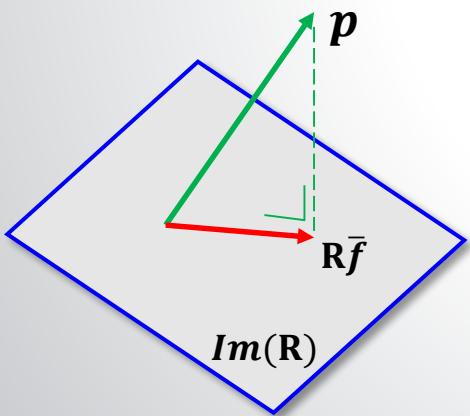
# Reconstruction

## ■ Modèle algébrique



$$p = \mathbf{R}f + s + n$$

$$p \notin \text{Im}(\mathbf{R}) \quad \exists \bar{f} : \mathbf{R}\bar{f} = p$$

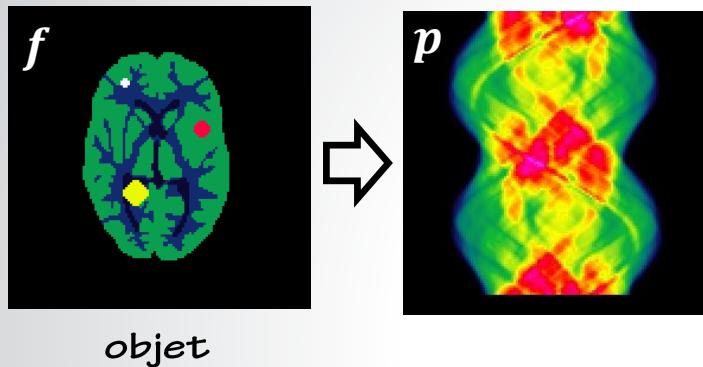


$$\bar{f} = \underset{f \in \Omega}{\operatorname{argmin}} \{\|\mathbf{R}f - p\|\}$$

$$\bar{f} = (\mathbf{R}^* \mathbf{R})^{-1} \mathbf{R}^* p$$

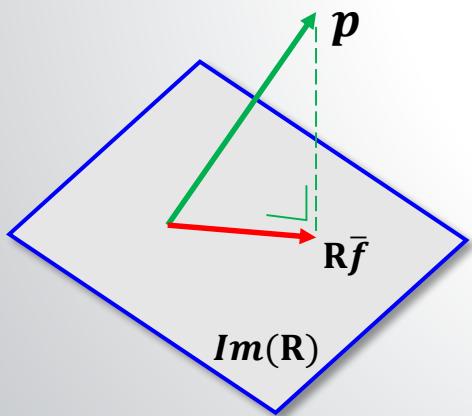
# Reconstruction

## ■ Modèle algébrique



$$p = \mathbf{R}f + s + n$$

$$p \notin \text{Im}(\mathbf{R}) \quad \exists \bar{f} : \mathbf{R}\bar{f} = p$$



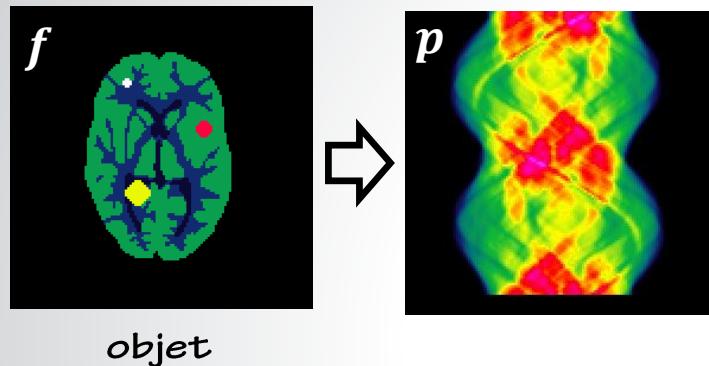
$$\bar{f} = \underset{f \in \Omega}{\operatorname{argmin}} \{\|\mathbf{R}f - p\|\}$$

$$\bar{f} = (\mathbf{R}^* \mathbf{R})^{-1} \mathbf{R}^* p$$

$$\dim(\mathbf{R}^* \mathbf{R}) = \sigma(10^5)$$
$$\kappa(\mathbf{R}^* \mathbf{R}) \gg$$

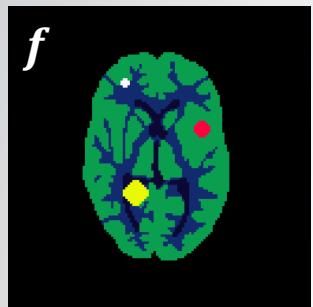
# Reconstruction

## ■ Méthodes itératives

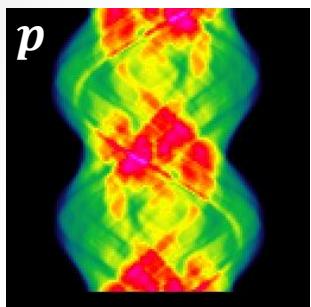


# Reconstruction

## ■ Méthodes itératives

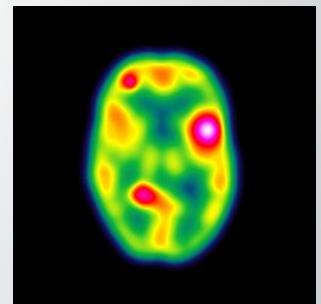


objet



$$\bar{p}^0 = \mathbf{R}\bar{f}^0(+s)$$

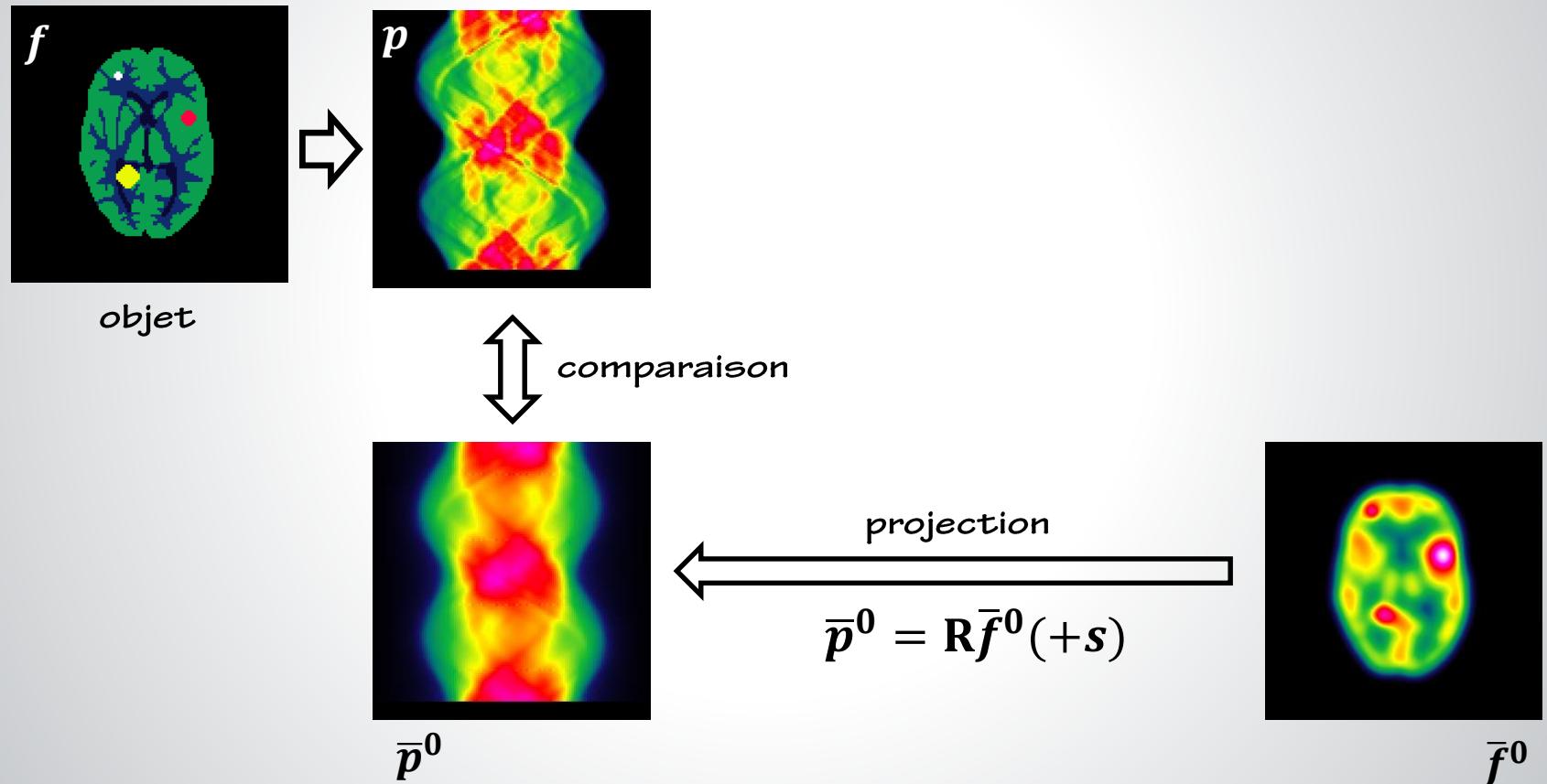
estimation



$\bar{f}^0$

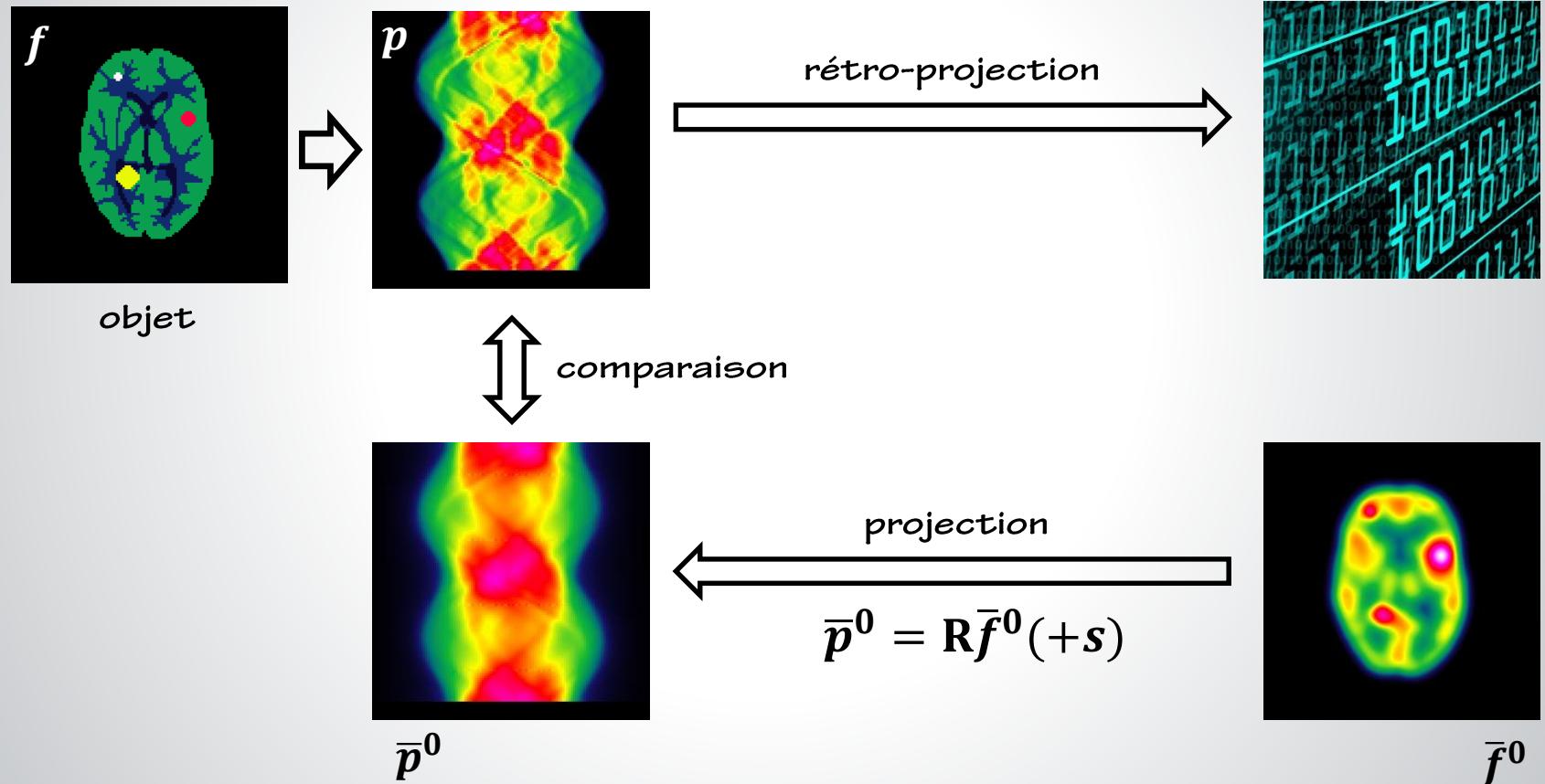
# Reconstruction

## ■ Méthodes itératives



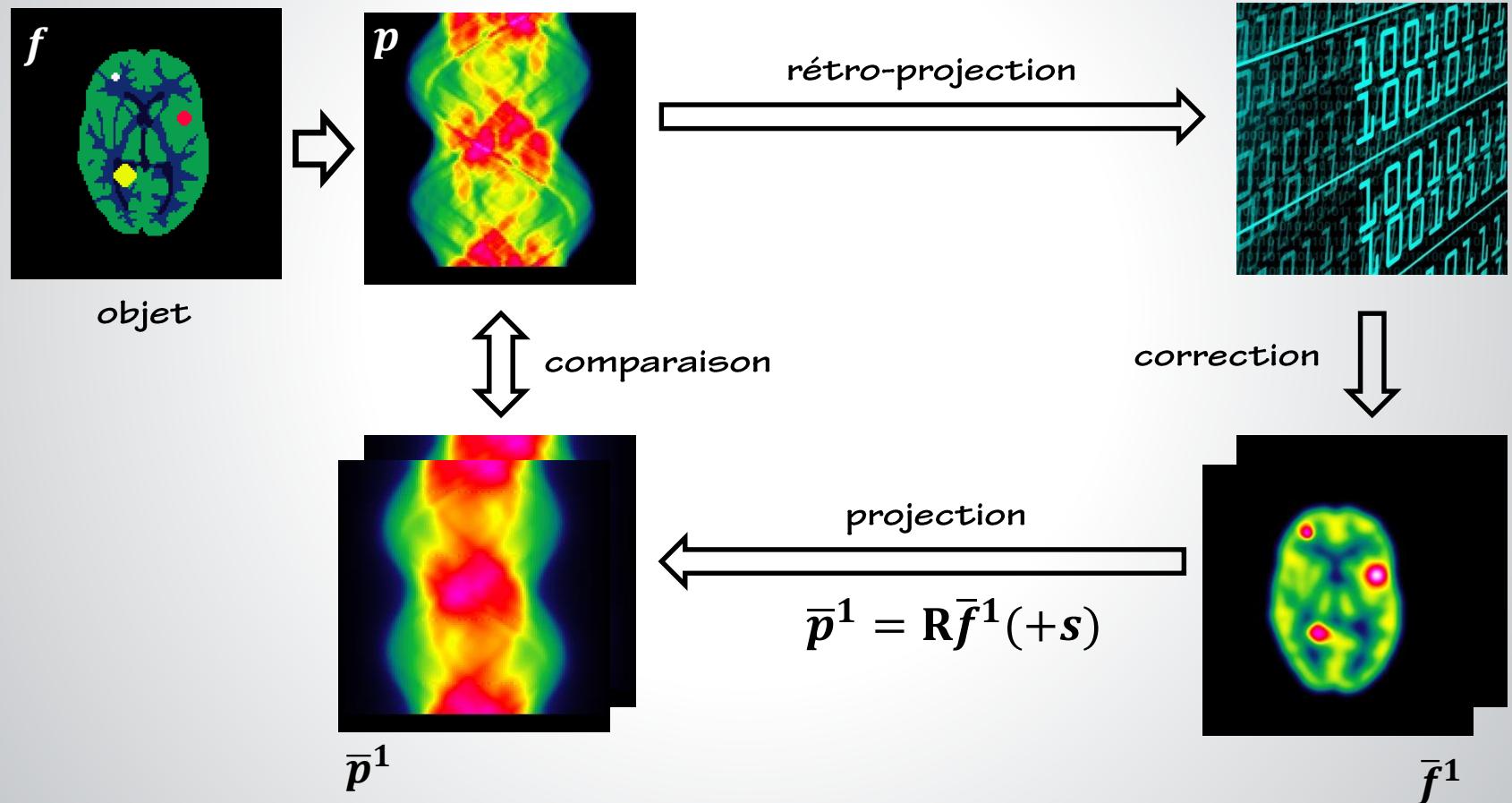
# Reconstruction

## ■ Méthodes itératives



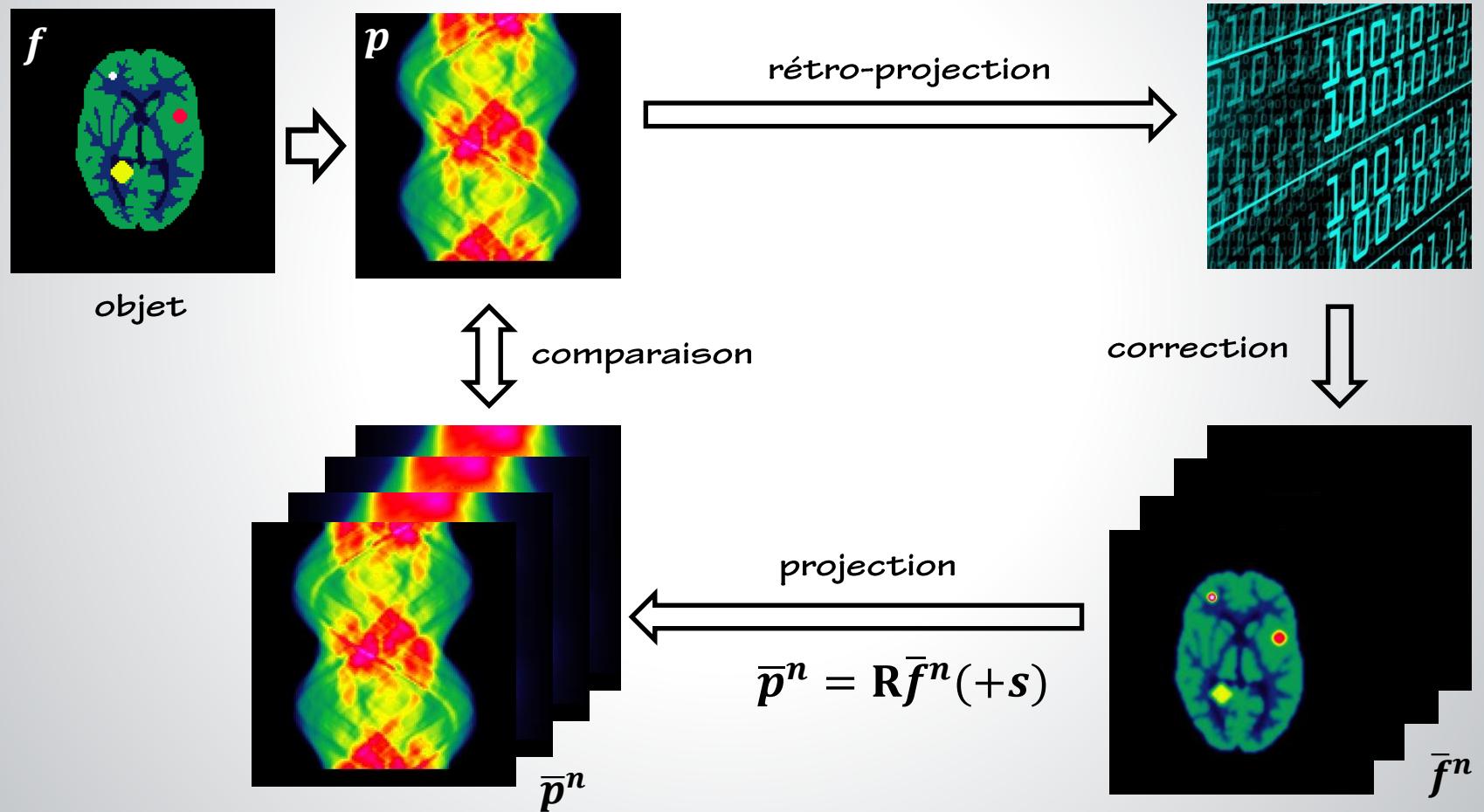
# Reconstruction

## ■ Méthodes itératives



# Reconstruction

## ■ Méthodes itératives



# Reconstruction

## ■ Méthodes itératives



$$\bar{f} = \underset{f \in \Omega}{\operatorname{argmin}} \{ J(f) \}$$

$$J(f) = \| \mathbf{R}f - p \|^2$$

Méthode LS

# Reconstruction

## ■ Méthodes itératives



$$\bar{f} = \underset{f \in \Omega}{\operatorname{argmin}} \{ J(f) \}$$

$$J(f) = \|Rf - p\|^2$$

Méthode LS

$$\bar{f} = (\mathbf{R}^* \mathbf{R})^{-1} \mathbf{R}^* p$$

$$\dim(\mathbf{R}^* \mathbf{R}) = \sigma(10^5)$$

$$\kappa(\mathbf{R}^* \mathbf{R}) \gg$$

# Reconstruction

## ■ Méthodes itératives



$$\bar{f} = \underset{f \in \Omega}{\operatorname{argmin}} \{ J(f) \}$$

$$J(f) = \| \mathbf{R}f - p \|^2$$

Méthode LS

$$\bar{f} = (\mathbf{R}^* \mathbf{R})^{-1} \mathbf{R}^* p$$

$$\bar{f}^{n+1} = \bar{f}^n + \eta \mathbf{R}^* (p - \mathbf{R} \bar{f}^n)$$

# Reconstruction

## ■ Méthodes itératives



$$\bar{f} = \underset{f \in \Omega}{\operatorname{argmin}} \{ J(f) \}$$

$$J(f) = \|Rf - p\|^2$$

Méthode LS

$$\bar{f} = (R^* R)^{-1} R^* p$$

$$\bar{f}^{n+1} = \bar{f}^n + \eta R^* (p - R \bar{f}^n)$$

correction additive

# Reconstruction

## ■ Méthodes itératives



$$\bar{f} = \underset{f \in \Omega}{\operatorname{argmin}} \{ J(f) \}$$

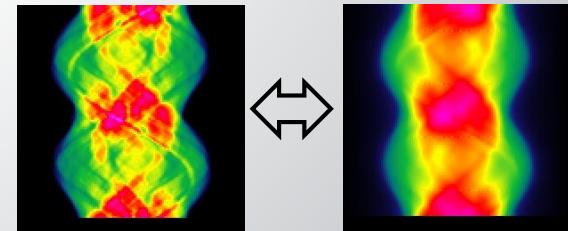
$$J(f) = \| \mathbf{R}f - p \|^2$$

Méthode LS

$$\bar{f} = (\mathbf{R}^* \mathbf{R})^{-1} \mathbf{R}^* p$$

$$\bar{f}^{n+1} = \bar{f}^n + \eta \mathbf{R}^* (p - \mathbf{R} \bar{f}^n)$$

comparaison



# Reconstruction

## ■ Méthodes itératives



$$\bar{f} = \underset{f \in \Omega}{\operatorname{argmin}} \{ J(f) \}$$

$$J(f) = \| \mathbf{R}f - p \|^2$$

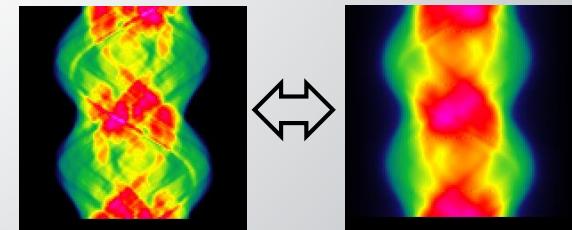
Méthode LS

$$\bar{f} = (\mathbf{R}^* \mathbf{R})^{-1} \mathbf{R}^* p$$

$$\bar{f}^{n+1} = \bar{f}^n + \eta \mathbf{R}^* (p - \mathbf{R} \bar{f}^n)$$

rétro-projection

comparaison



# Reconstruction

## ■ Méthodes itératives



$$\bar{f} = \underset{f \in \Omega}{\operatorname{argmin}} \{ J(f) \}$$

$$J(f) = -\log\{ \wp(p|f) \}$$

Méthode ML

# Reconstruction

## ■ Méthodes itératives



$$\bar{f} = \underset{f \in \Omega}{\operatorname{argmin}} \{ J(f) \}$$

$$J(f) = -\log \{ \wp(p|f) \}$$

$$\wp(p|f) = \prod_i \frac{e^{-\tilde{p}_i} \tilde{p}_i^{p_i}}{p_i!}$$
$$\tilde{p}_i = (\mathbf{R}f)_i$$

Méthode ML

# Reconstruction

## ■ Méthodes itératives



$$\bar{f} = \underset{f \in \Omega}{\operatorname{argmin}} \{ J(f) \}$$

$$J(f) = -\log \{ \wp(p|f) \}$$

$$\wp(p|f) = \prod_i \frac{e^{-\tilde{p}_i} \tilde{p}_i^{p_i}}{p_i!}$$
$$\tilde{p}_i = (\mathbf{R}f)_i$$

Méthode ML

$$J(f) = \sum_i \{ \mathbf{R}f_i - p_i \log(\mathbf{R}f_i) \}$$

# Reconstruction

## ■ Méthodes itératives



$$\bar{f} = \underset{f \in \Omega}{\operatorname{argmin}} \{ J(f) \}$$

$$J(f) = -\log\{ \wp(p|f) \}$$

Méthode ML

$$J(f) = \sum_i \{ \mathbf{R}f_i - p_i \log(\mathbf{R}f_i) \}$$

$$\bar{f}^{n+1} = \bar{f}^n \times \left( \mathbf{R}^* \frac{\mathbf{p}}{\mathbf{R} \bar{f}^n} \right)$$

# Reconstruction

## ■ Méthodes itératives



$$\bar{f} = \underset{f \in \Omega}{\operatorname{argmin}} \{ J(f) \}$$

$$J(f) = -\log\{ \wp(p|f) \}$$

Méthode ML

$$J(f) = \sum_i \{ \mathbf{R}f_i - p_i \log(\mathbf{R}f_i) \}$$

$$\bar{f}^{n+1} = \bar{f}^n \times \left( \mathbf{R}^* \frac{\mathbf{p}}{\mathbf{R} \bar{f}^n} \right)$$

correction multiplicative

# Reconstruction

## ■ Méthodes itératives



$$\bar{f} = \underset{f \in \Omega}{\operatorname{argmin}} \{ J(f) \}$$

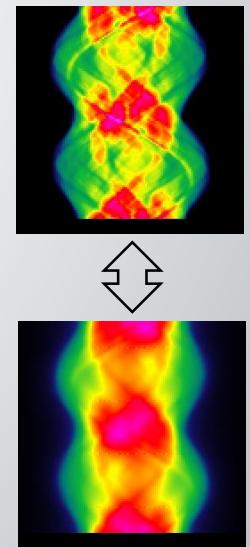
$$J(f) = -\log \{ \wp(p|f) \}$$

### Méthode ML

$$J(f) = \sum_i \{ \mathbf{R}f_i - p_i \log(\mathbf{R}f_i) \}$$

$$\bar{f}^{n+1} = \bar{f}^n \times \left( \mathbf{R}^* \frac{\mathbf{p}}{\mathbf{R} \bar{f}^n} \right)$$

comparaison



# Reconstruction

## ■ Méthodes itératives



$$\bar{f} = \underset{f \in \Omega}{\operatorname{argmin}} \{ J(f) \}$$

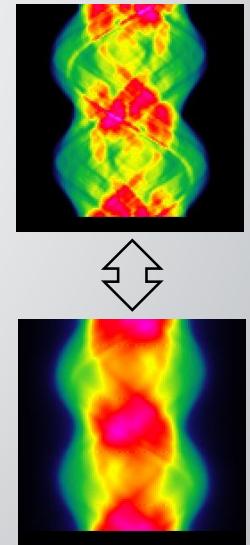
$$J(f) = -\log \{ \wp(p|f) \}$$

### Méthode ML

$$J(f) = \sum_i \{ \mathbf{R}f_i - p_i \log(\mathbf{R}f_i) \}$$

$$\bar{f}^{n+1} = \bar{f}^n \times \left( \begin{array}{c|c} \mathbf{R}^* & p \\ \hline & \mathbf{R} \bar{f}^n \end{array} \right)$$

rétro-projection                      comparaison



# Régularisation

$$p = Rf$$

*R est mal conditionné :  $\kappa(R) \gg$*

# Régularisation

$$p = Rf$$

*R est mal conditionné :  $\kappa(R) \gg$*

$$\frac{\|\Delta f\|}{\|f\|} \leq \kappa(R) \frac{\|\Delta p\|}{\|p\|} \approx \sigma \left( \frac{1}{\sqrt{p}} \right)$$

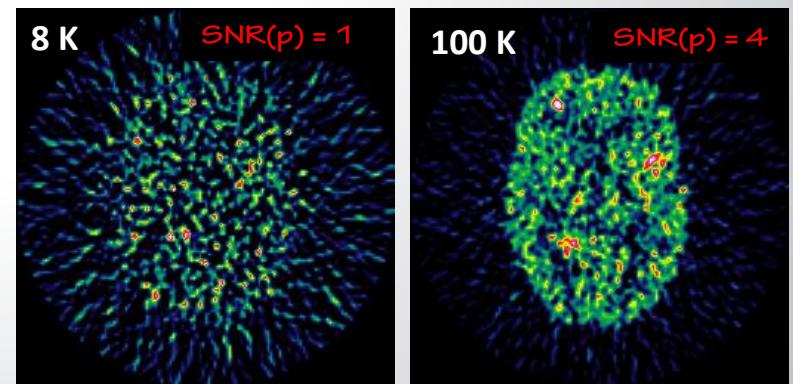
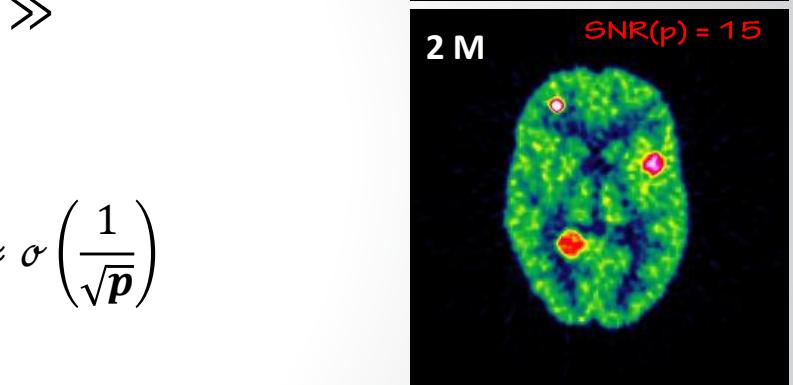
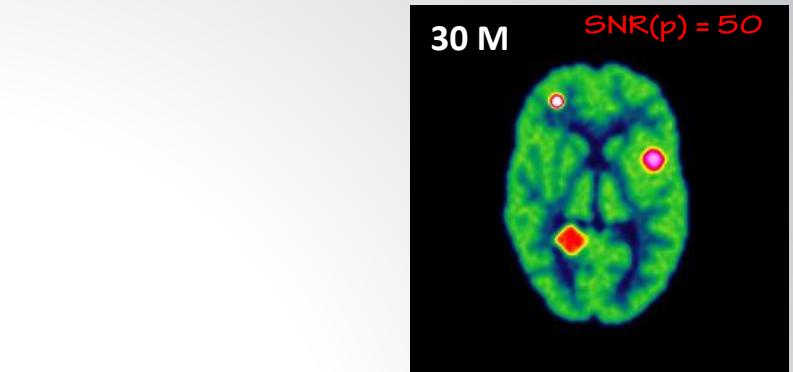
# Régularisation

$$p = Rf$$

*R est mal conditionné :  $\kappa(R) \gg$*

$$\frac{\|\Delta f\|}{\|f\|} \leq \kappa(R) \frac{\|\Delta p\|}{\|p\|} \approx \sigma \left( \frac{1}{\sqrt{p}} \right)$$

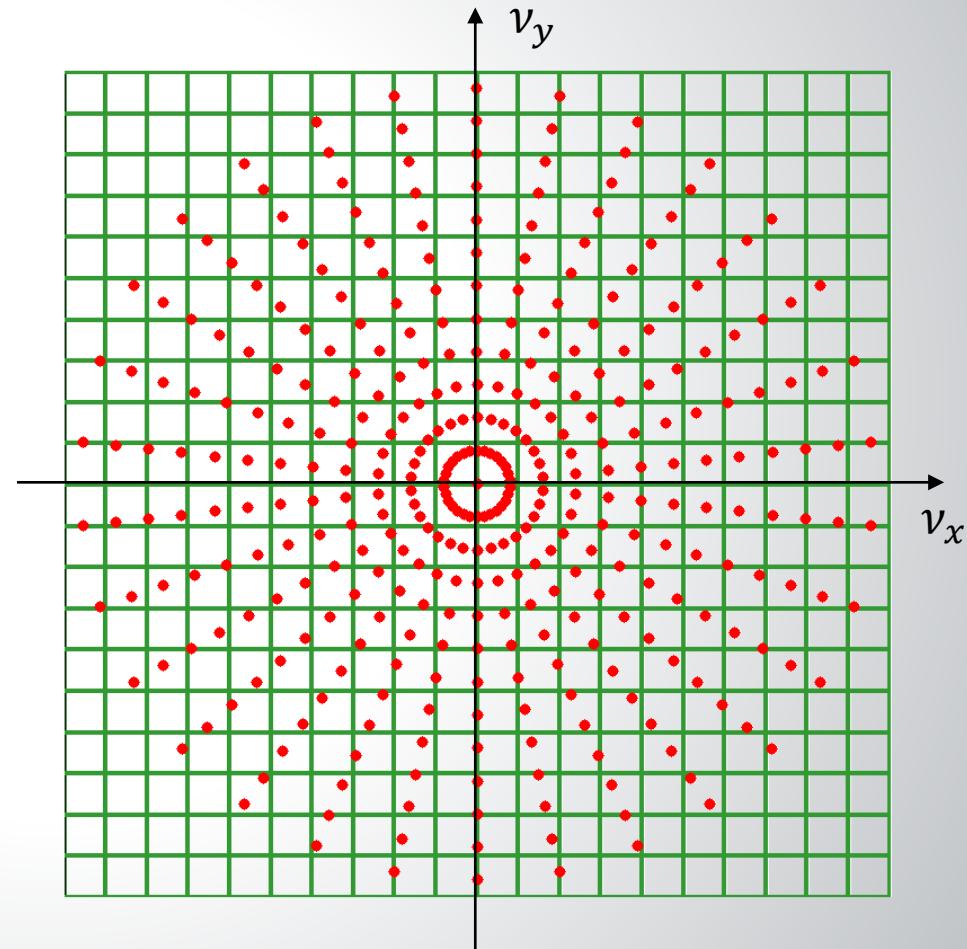
➡ Sensibilité au bruit



# Régularisation

## ■ Reconstruction analytique

$$\hat{f}(v \cos \theta, v \sin \theta) = \hat{p}_\theta(v)$$

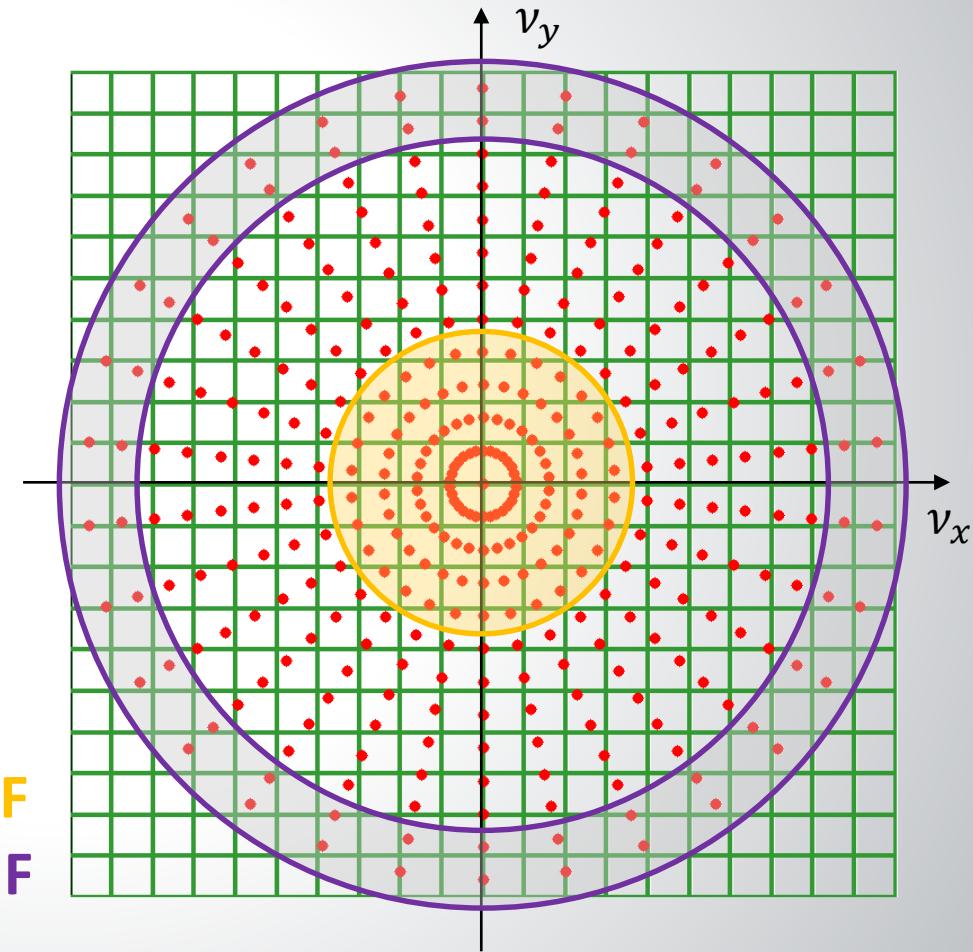


# Régularisation

## ■ Reconstruction analytique

$$\hat{f}(v \cos \theta, v \sin \theta) = \hat{p}_\theta(v)$$

BF  
HF

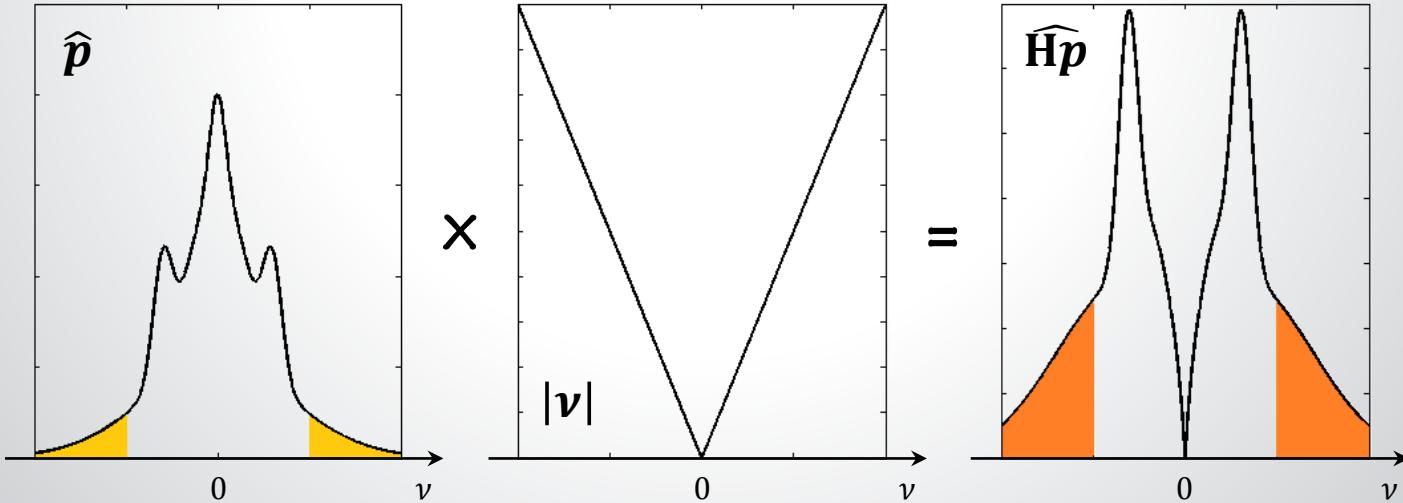
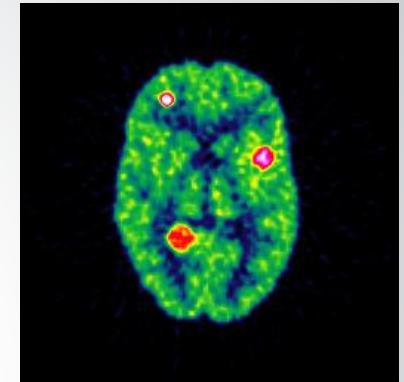


# Régularisation

## ■ Reconstruction analytique

$$f = \mathbf{R}^* \mathbf{H} p$$

$$\widehat{\mathbf{H} p} = |\nu| \widehat{p}$$

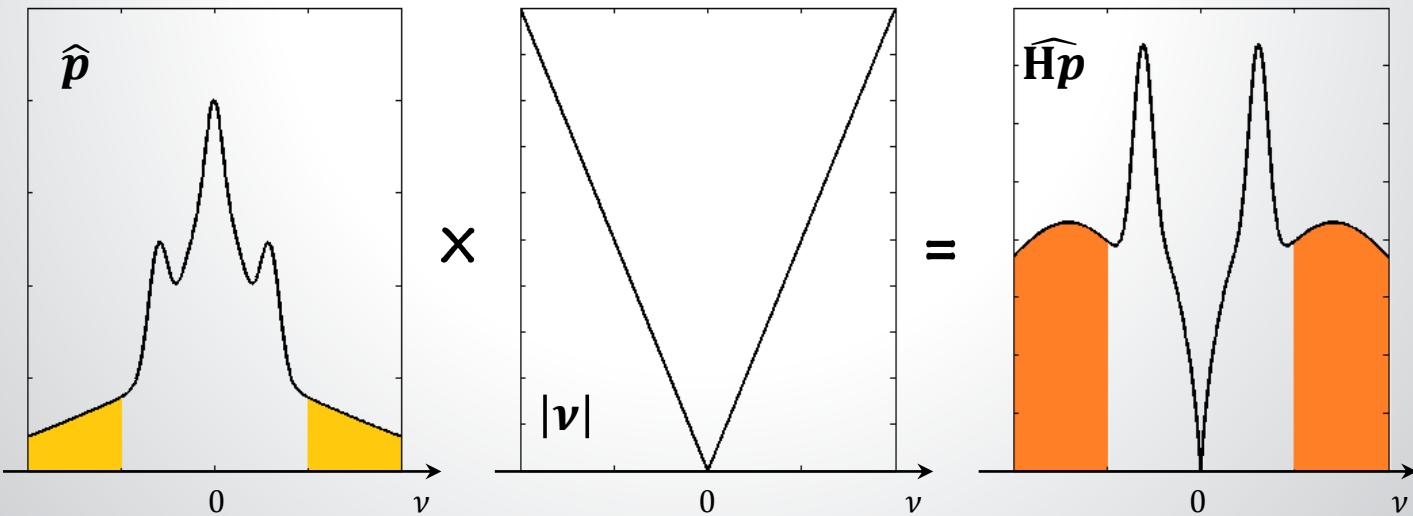
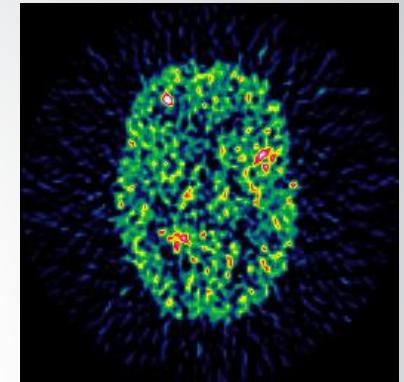


# Régularisation

## ■ Reconstruction analytique

$$f = \mathbf{R}^* \mathbf{H} p$$

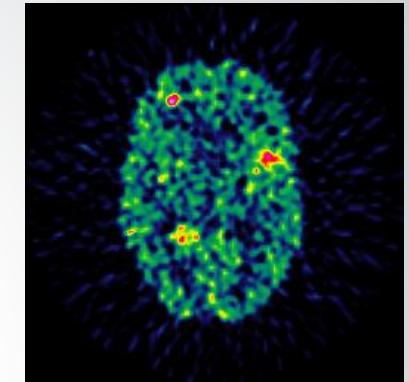
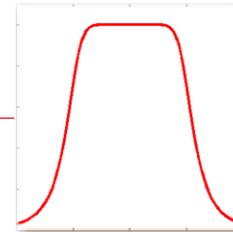
$$\widehat{\mathbf{H} p} = |\nu| \widehat{p}$$



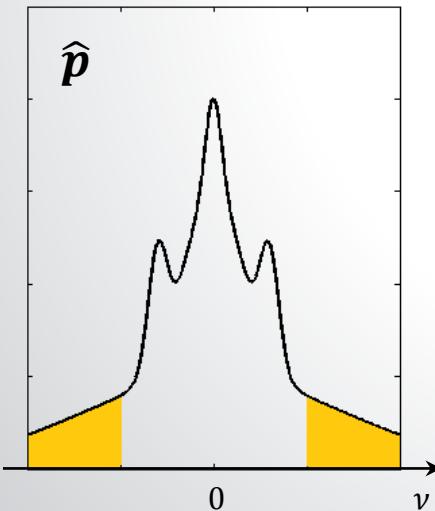
# Régularisation

## ■ Reconstruction analytique

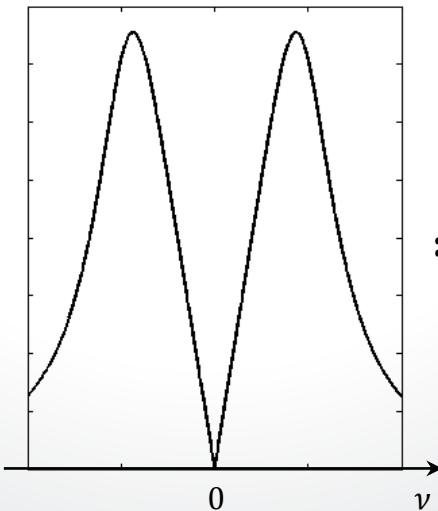
$$f = \mathbf{R}^* \mathbf{B} \mathbf{H} p \quad \widehat{\mathbf{B} \mathbf{H} p} = \frac{|\nu| \widehat{p}}{\sqrt{1 + \left(\frac{\nu}{\nu_c}\right)^\beta}}$$



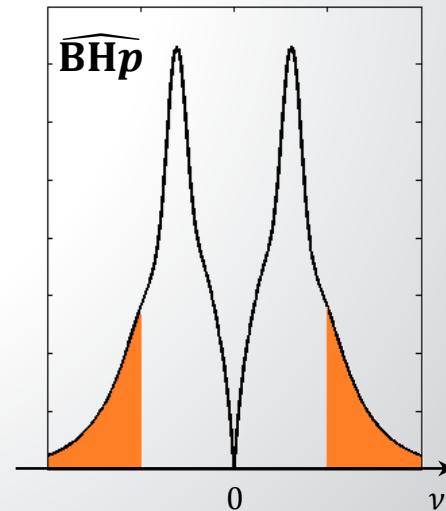
$$\nu_c = 0,5$$



$\times$



$=$

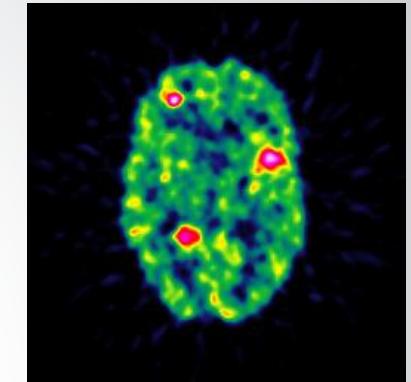
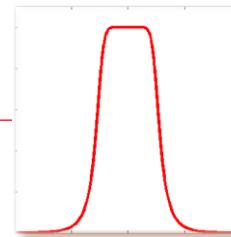


# Régularisation

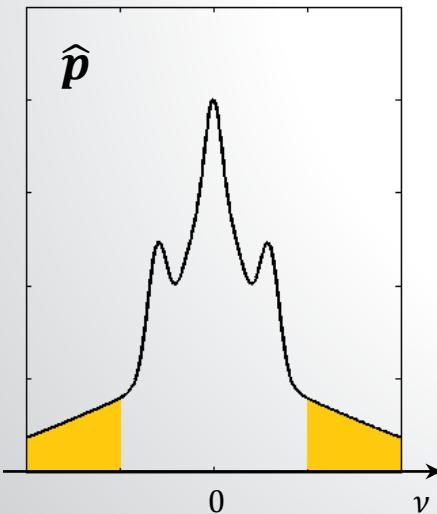
## ■ Reconstruction analytique

$$f = \mathbf{R}^* \mathbf{B} \mathbf{H} p \quad \widehat{\mathbf{B} \mathbf{H} p} =$$

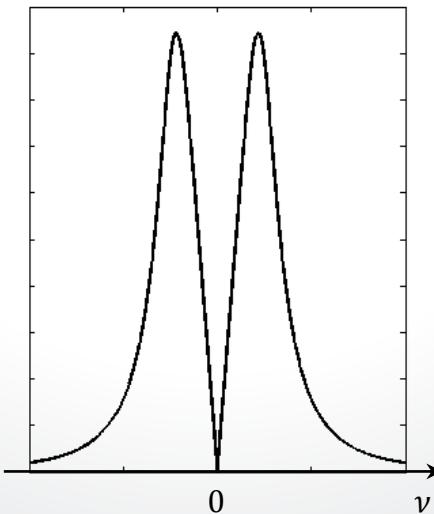
$$\frac{|\nu| \widehat{p}}{\sqrt{1 + \left(\frac{\nu}{\nu_c}\right)^\beta}}$$



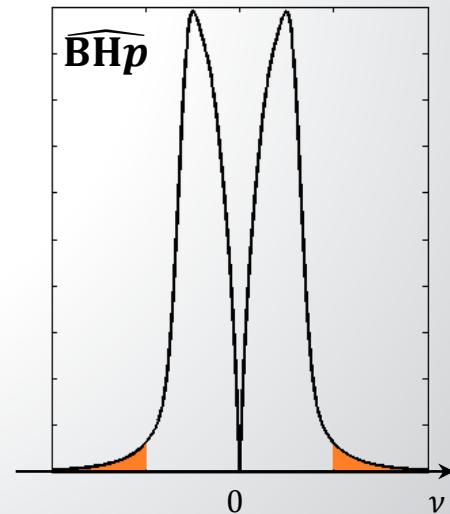
$$\nu_c = 0,25$$



$\times$

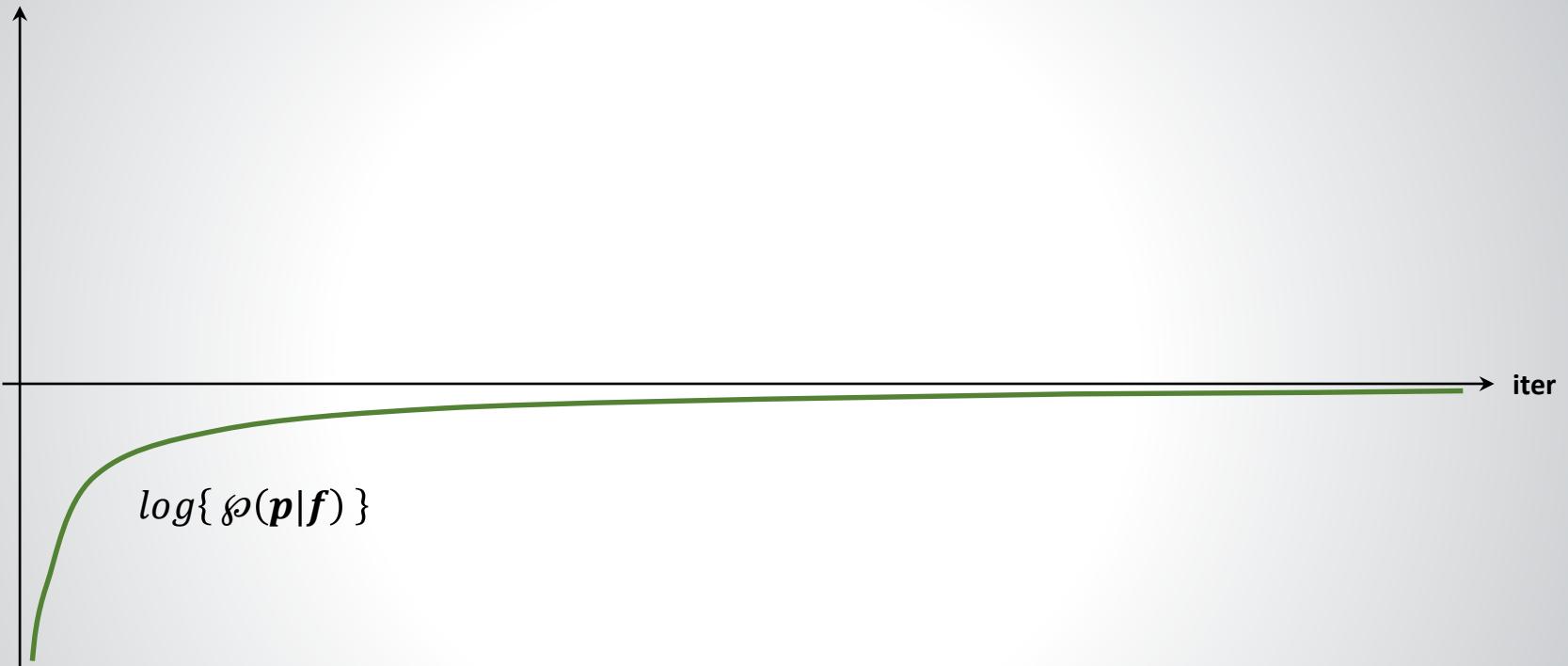


$=$



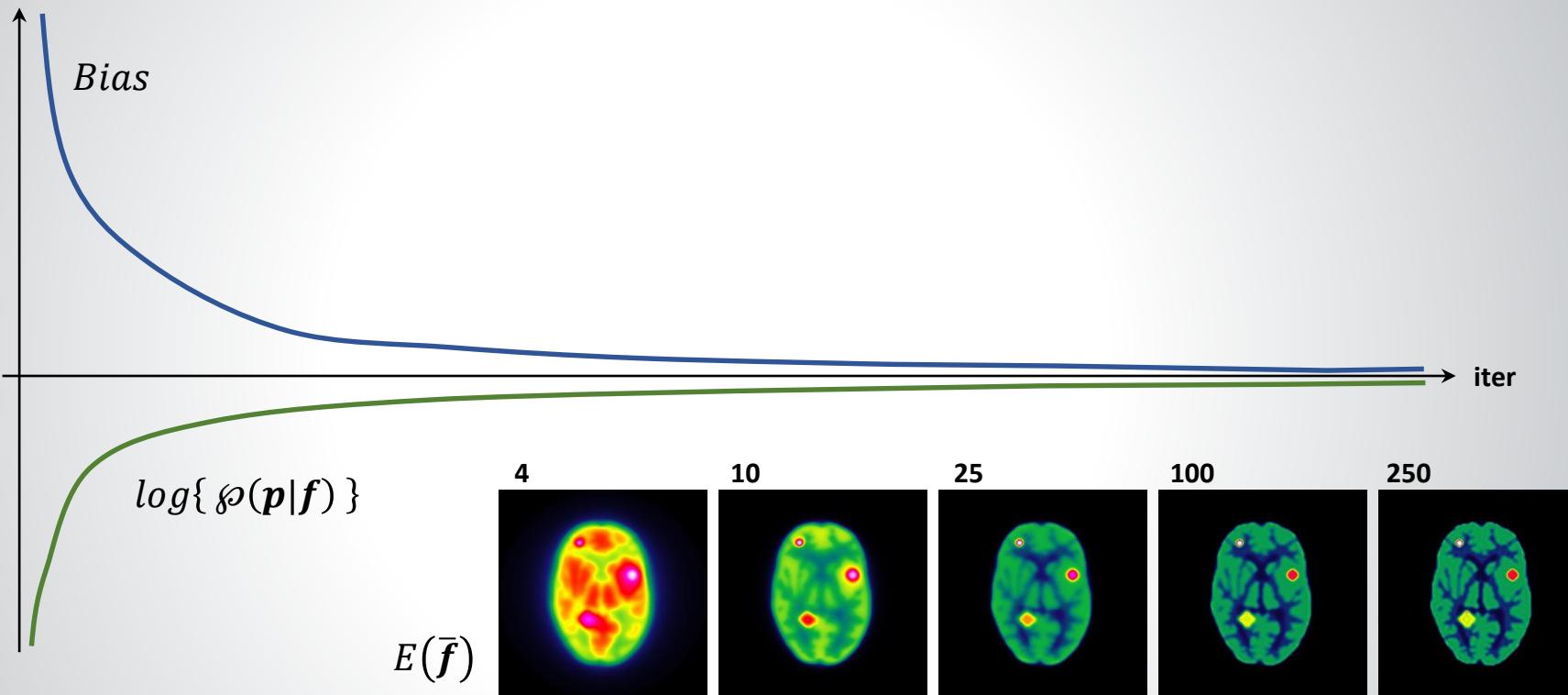
# Régularisation

## ■ Reconstruction itérative



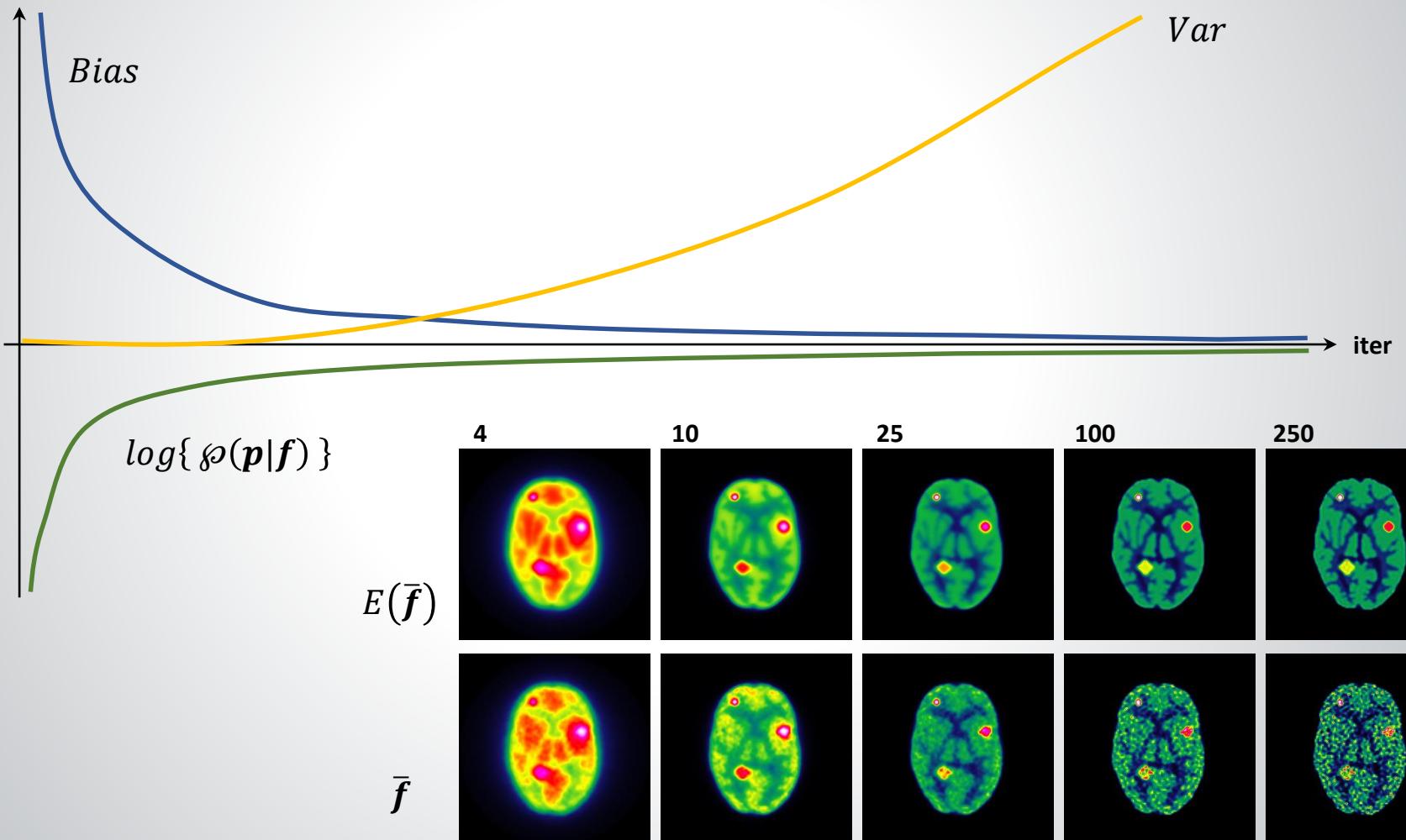
# Régularisation

## ■ Reconstruction itérative



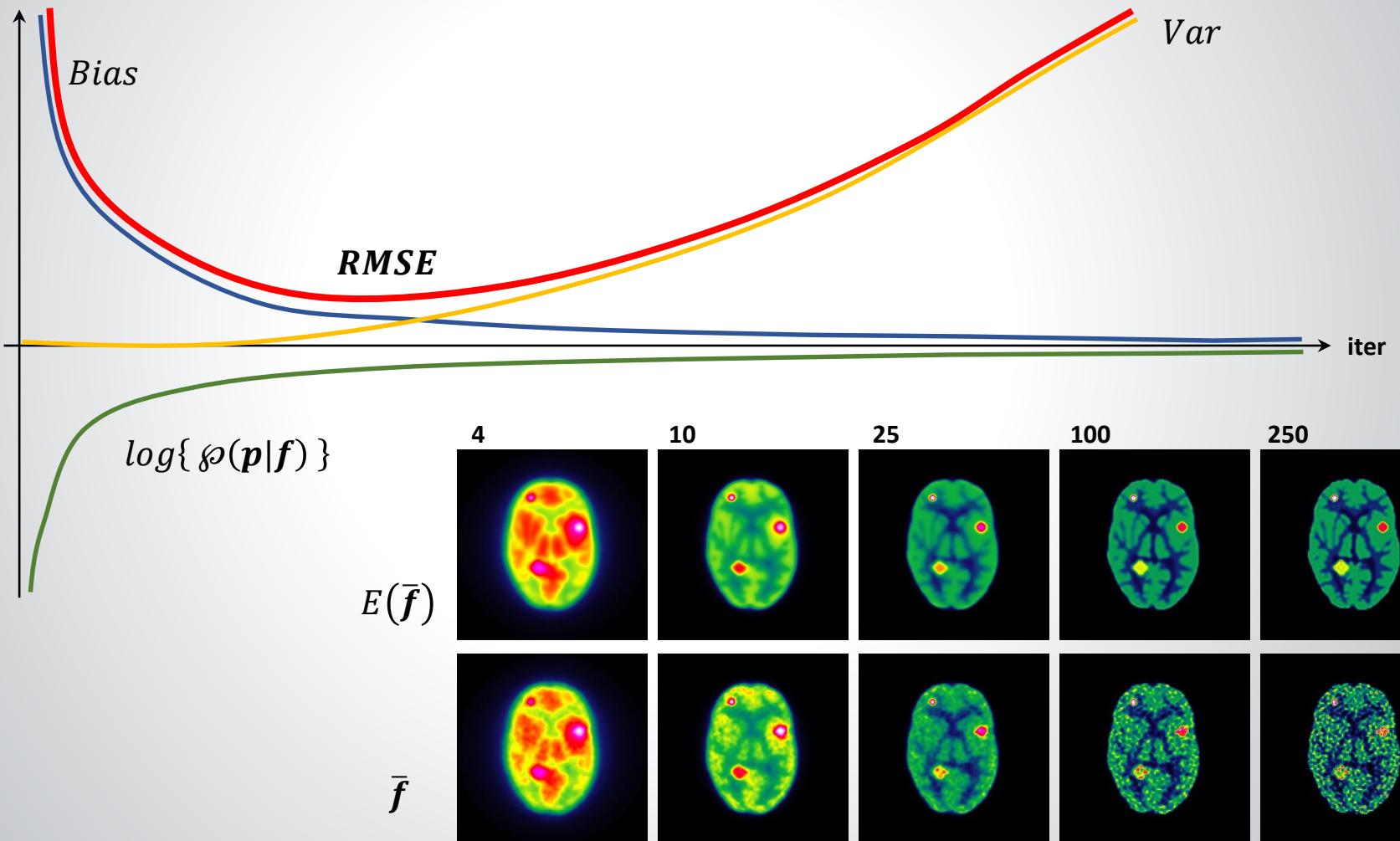
# Régularisation

## ■ Reconstruction itérative



# Régularisation

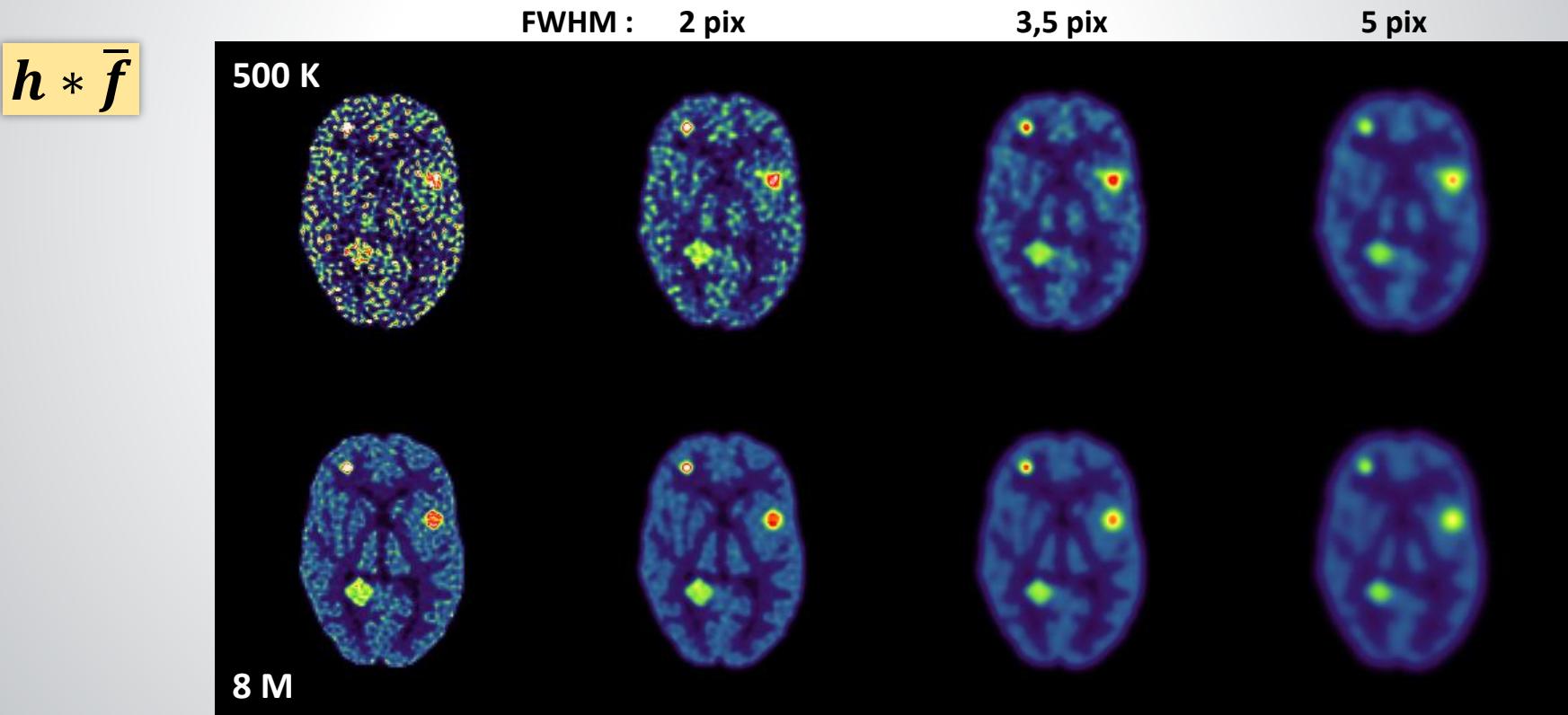
## ■ Reconstruction itérative



# Régularisation

## ■ Reconstruction itérative

Post-filtrage



# Régularisation

## ■ Reconstruction itérative

Tikhonov

$$\bar{f} = \underset{f \in C}{\operatorname{argmin}} \{J(f)\}$$

$$J(f) = \|\mathbf{R}f - p\|^2 + \rho(f)$$

# Régularisation

## ■ Reconstruction itérative

Tikhonov

$$\bar{f} = \underset{f \in C}{\operatorname{argmin}} \{J(f)\}$$

$$J(f) = \|\mathbf{R}f - p\|^2 + \rho(f)$$

Adéquation  
Surjectivité  
↓ biais

# Régularisation

## ■ Reconstruction itérative

Tikhonov

$$\bar{f} = \underset{f \in C}{\operatorname{argmin}} \{J(f)\}$$

$$J(f) = \|\mathbf{R}f - p\|^2 + \rho(f)$$

Adéquation  
Surjectivité  
↓ biais

Régularisation  
Injectivité  
↓ variance

# Régularisation

## ■ Reconstruction itérative

Tikhonov

$$\bar{f} = \underset{f \in C}{\operatorname{argmin}} \{J(f)\}$$

$$J(f) = \|\mathbf{R}f - p\|^2 + \beta \|f\|^2$$

# Régularisation

## ■ Reconstruction itérative

Tikhonov

$$\bar{f} = \underset{f \in C}{\operatorname{argmin}} \{J(f)\}$$

$$J(f) = \|\mathbf{R}f - p\|^2 + \beta \|f\|^2$$

$$\bar{f} = (\mathbf{R}^* \mathbf{R} + \beta \mathbf{I})^{-1} \mathbf{R}^* p$$

$$\bar{f}^{n+1} = (1 - \beta) \bar{f}^n + \eta \mathbf{R}^* (p - \mathbf{R} \bar{f}^n)$$

# Régularisation

## ■ Reconstruction itérative

MAP

$$\bar{f} = \underset{f \in C}{\operatorname{argmin}} \{ J(f) \}$$

Posterior

$$J(f) = -\log \{ \wp(f|p) \}$$

# Régularisation

## ■ Reconstruction itérative

MAP

$$\bar{f} = \underset{f \in C}{\operatorname{argmin}} \{ J(f) \}$$

Posterior

$$J(f) = -\log \{ \wp(f|p) \}$$

$$\wp(f|p) = \frac{\wp(p|f) \wp(f)}{\wp(p)}$$

# Régularisation

## ■ Reconstruction itérative

MAP

$$\bar{f} = \underset{f \in C}{\operatorname{argmin}} \{ J(f) \}$$

Posterior

$$J(f) = -\log \{ \wp(f|p) \}$$

$$\wp(f|p) = \frac{\wp(p|f) \wp(f)}{\wp(p)}$$

$$J(f) = -\log \{ \wp(p|f) \} - \log \{ \wp(f) \}$$

# Régularisation

## ■ Reconstruction itérative

MAP

$$\bar{f} = \underset{f \in C}{\operatorname{argmin}} \{ J(f) \}$$

Posterior

$$J(f) = -\log \{ \wp(f|p) \}$$

Likelihood

$$J(f) = -\log \{ \wp(p|f) \} - \log \{ \wp(f) \}$$

Adéquation  
Surjectivité  
 $\downarrow$  biais

# Régularisation

## ■ Reconstruction itérative

MAP

$$\bar{f} = \underset{f \in C}{\operatorname{argmin}} \{ J(f) \}$$

Posterior

$$J(f) = -\log \{ \wp(f|p) \}$$

Likelihood

$$J(f) = -\log \{ \wp(p|f) \} - \log \{ \wp(f) \}$$

Prior

Adéquation  
Surjectivité  
 $\downarrow$  biais

Régularisation  
Injectivité  
 $\downarrow$  variance

# Régularisation

## ■ Reconstruction itérative

MAP

$$\bar{f} = \underset{f \in C}{\operatorname{argmin}} \{ J(f) \}$$

Posterior

$$J(f) = -\log \{ \wp(f|p) \}$$

Likelihood

Prior

$$J(f) = -\log \{ \wp(p|f) \} - \log \{ \wp(f) \}$$

$$\wp(f) = \kappa e^{-\beta U}$$

# Régularisation

## ■ Reconstruction itérative

MAP

$$\bar{f} = \underset{f \in C}{\operatorname{argmin}} \{ J(f) \}$$

Posterior

$$J(f) = -\log \{ \wp(f|p) \}$$

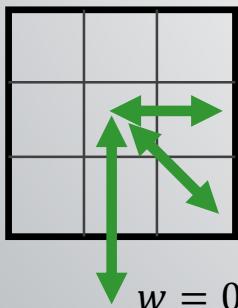
Likelihood

Prior

$$J(f) = -\log \{ \wp(p|f) \} - \log \{ \wp(f) \}$$

$$U = \sum_{i,j} w_{ij} \|f_i - f_j\|^2$$

$$\wp(f) = \kappa e^{-\beta U}$$



$$w_{1st} = 1$$

$$w_{2nd} = 1/\sqrt{2}$$

$$w = 0$$

# Régularisation

## ■ Reconstruction itérative

MAP

$$\bar{f} = \underset{f \in C}{\operatorname{argmin}} \{ J(f) \}$$

Posterior

$$J(f) = -\log \{ \wp(f|p) \}$$

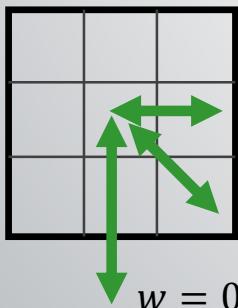
Likelihood

Prior

$$J(f) = -\log \{ \wp(p|f) \} - \log \{ \wp(f) \}$$

$$U = \sum_{i,j} w_{ij} \|f_i - f_j\|^2$$

$$\wp(f) = \kappa e^{-\beta U}$$



$$w_{1st} = 1$$

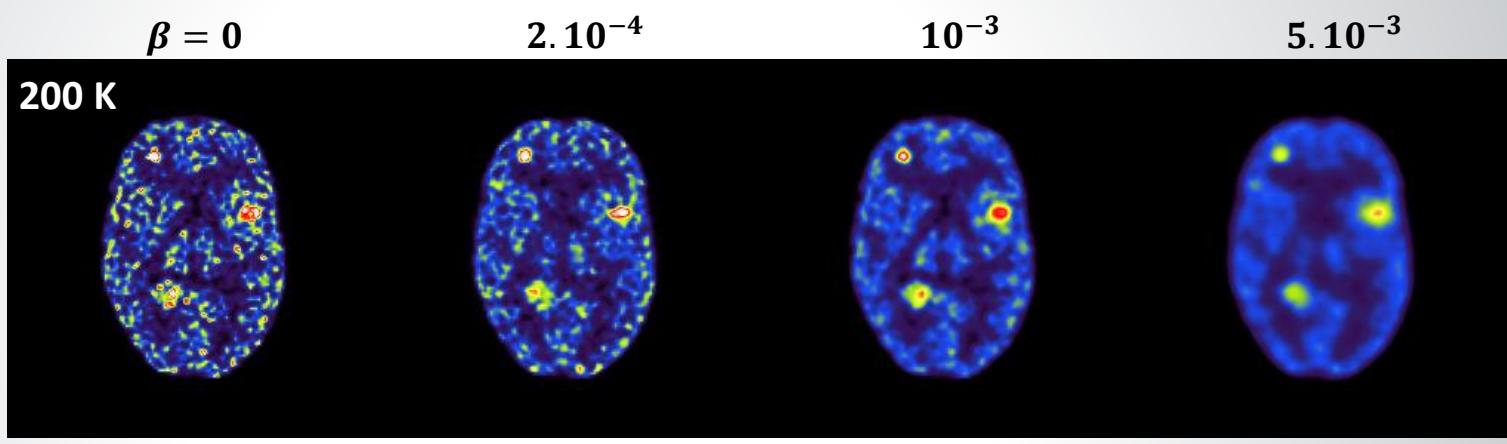
$$w_{2nd} = 1/\sqrt{2}$$

$$\bar{f}^{n+1} = \frac{\bar{f}^n}{1 + \beta \nabla U} \otimes \left( R^* \frac{p}{R \bar{f}^n} \right)$$

# Régularisation

## ■ Reconstruction itérative

MAP

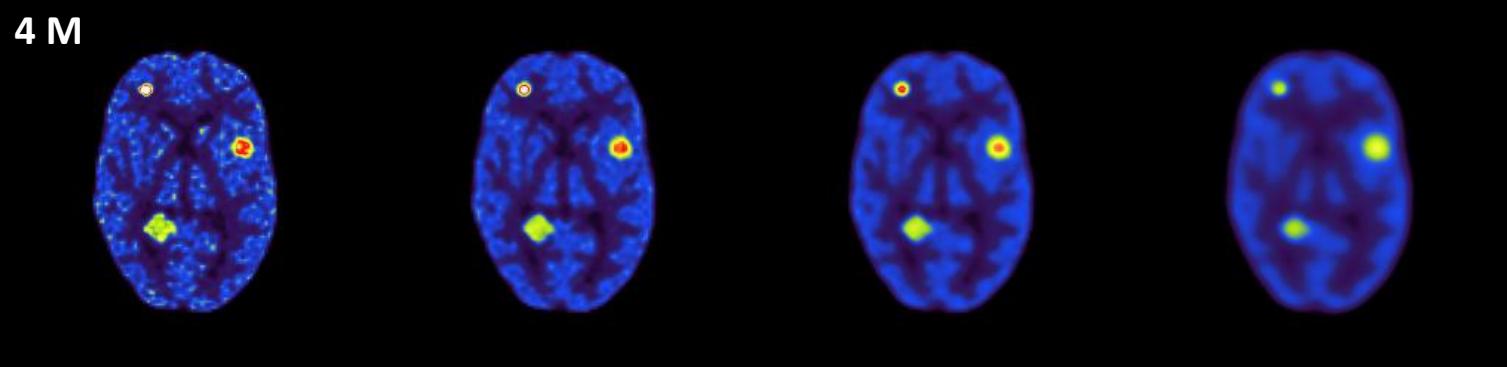


$\beta = 0$

$2 \cdot 10^{-4}$

$10^{-3}$

$5 \cdot 10^{-3}$



$\beta = 0$

$10^{-5}$

$5 \cdot 10^{-5}$

$2, 5 \cdot 10^{-4}$

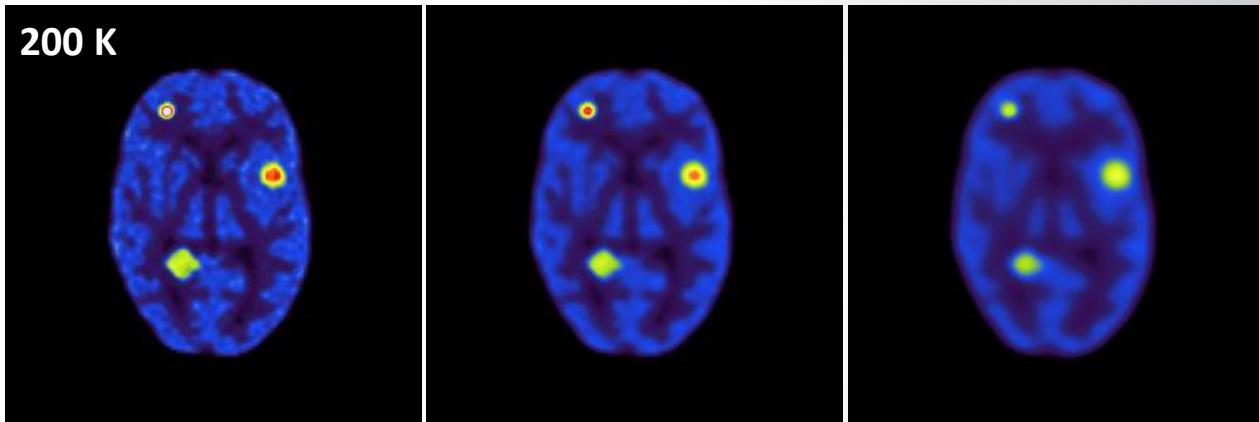
# Régularisation

## ■ Reconstruction itérative

MAP

Quad. prior

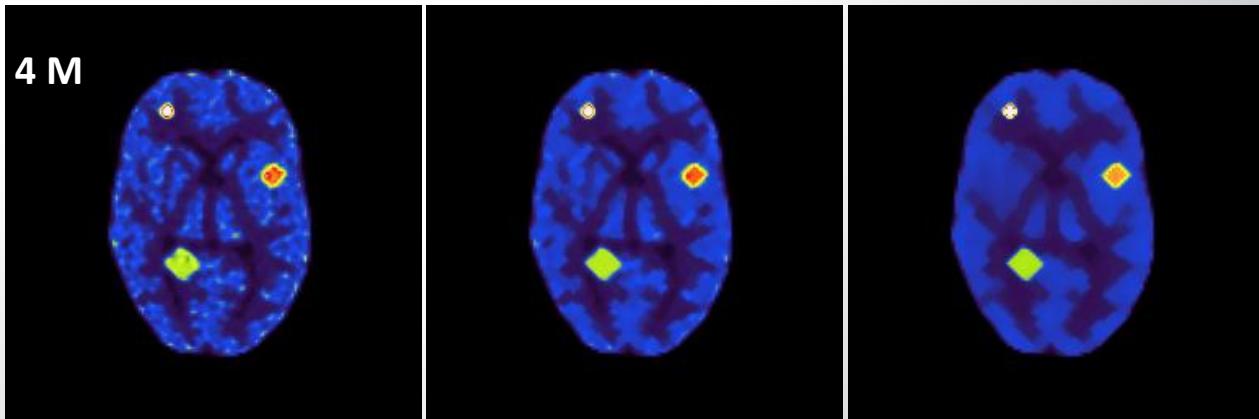
$$U = \sum_{i,j} w_{ij} \|f_i - f_j\|^2$$



Median prior

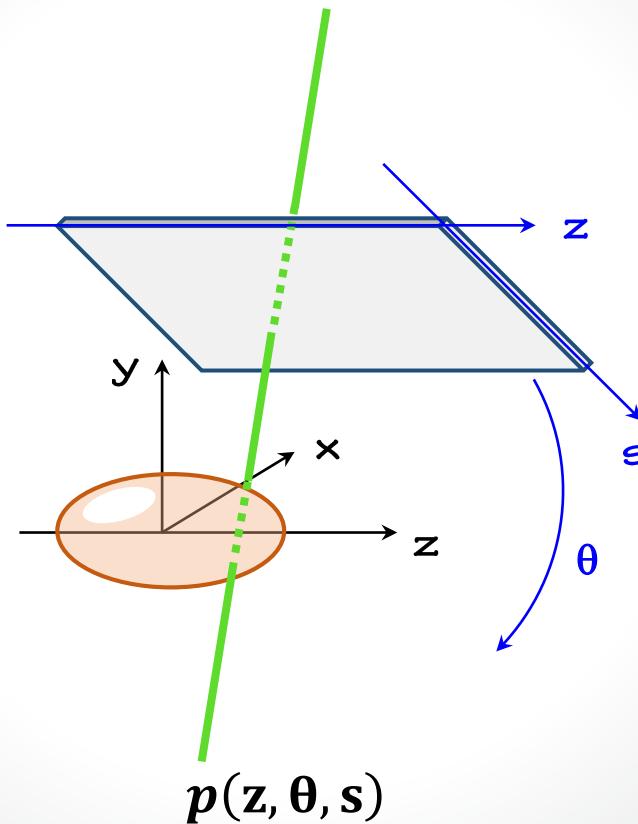
$$U = \sum_{i,j} w_{ij} |f_i - f_j|$$

« edge-preserving »



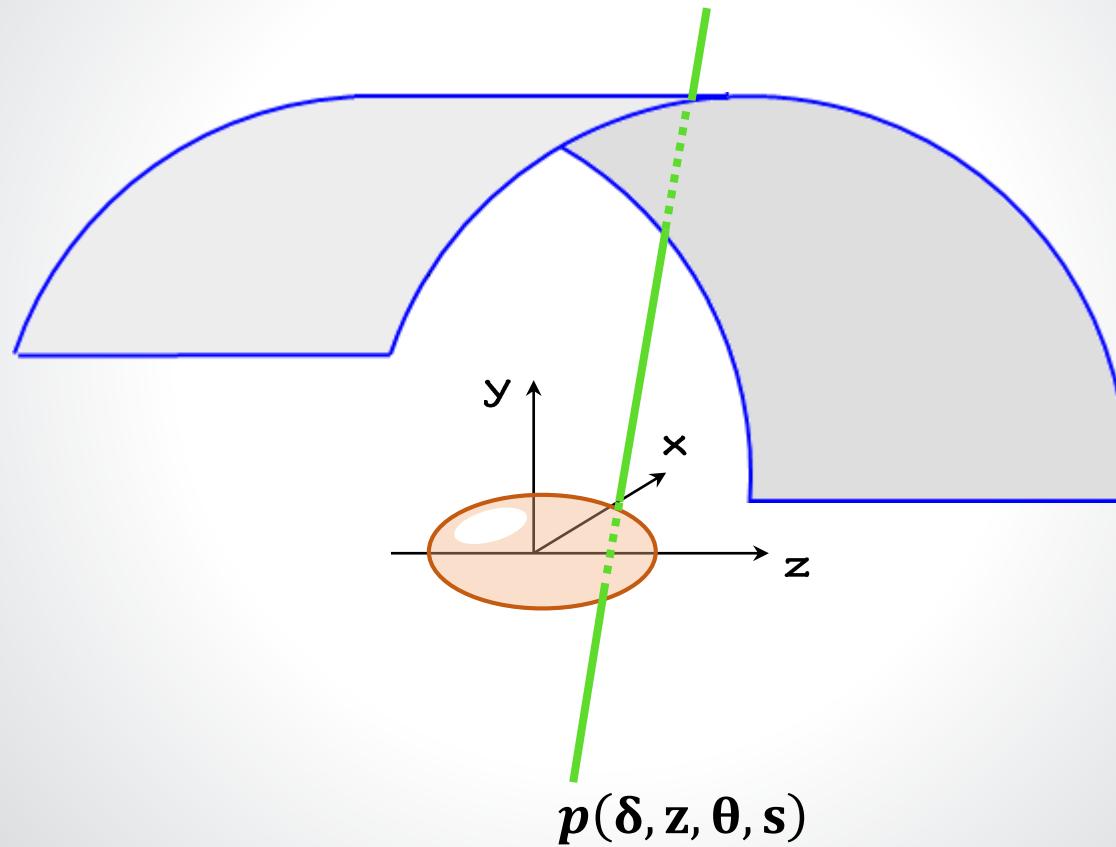
# TEP 3D

## ■ Encodage TEMP



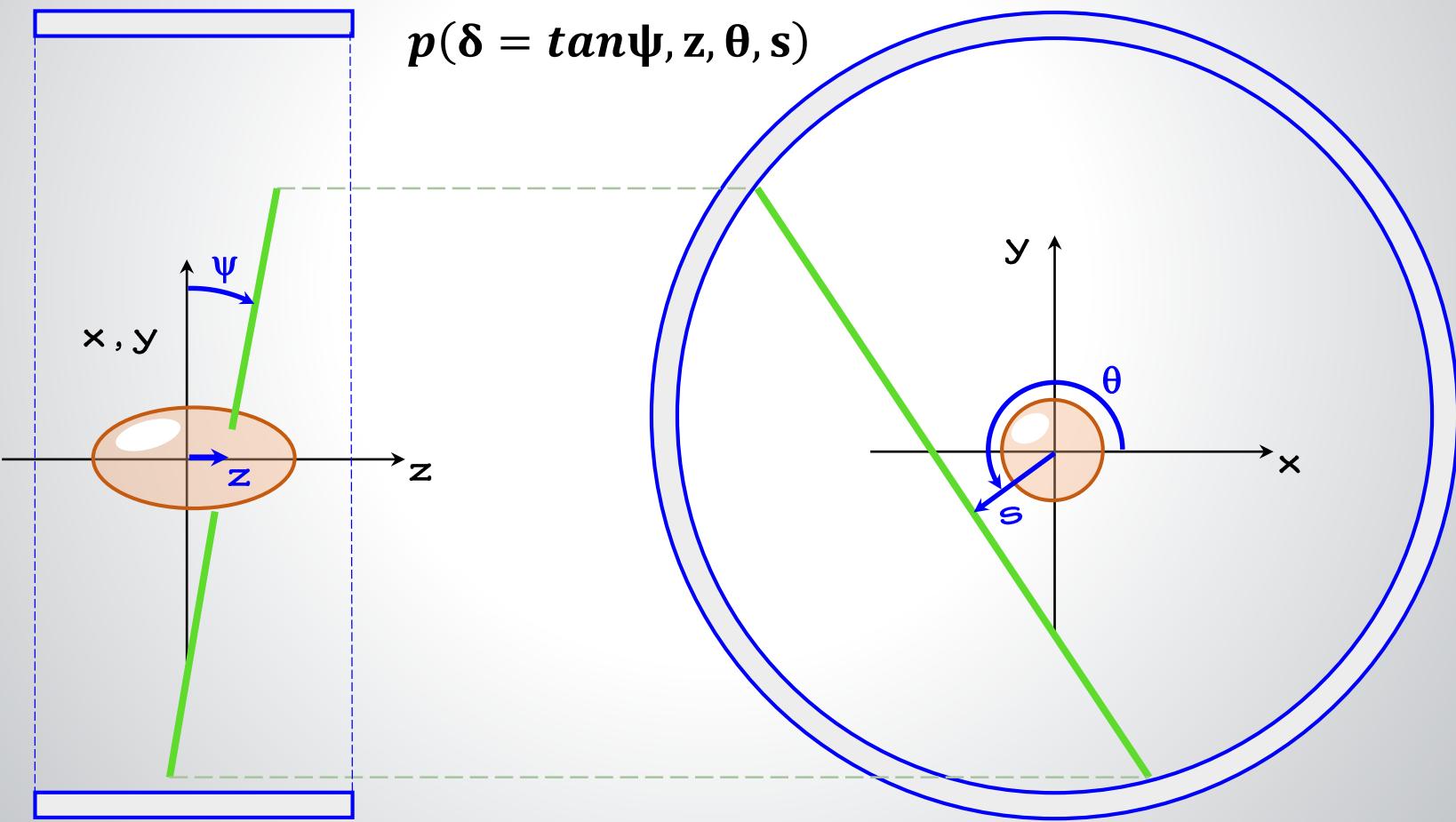
# TEP 3D

## ■ Encodage TEP



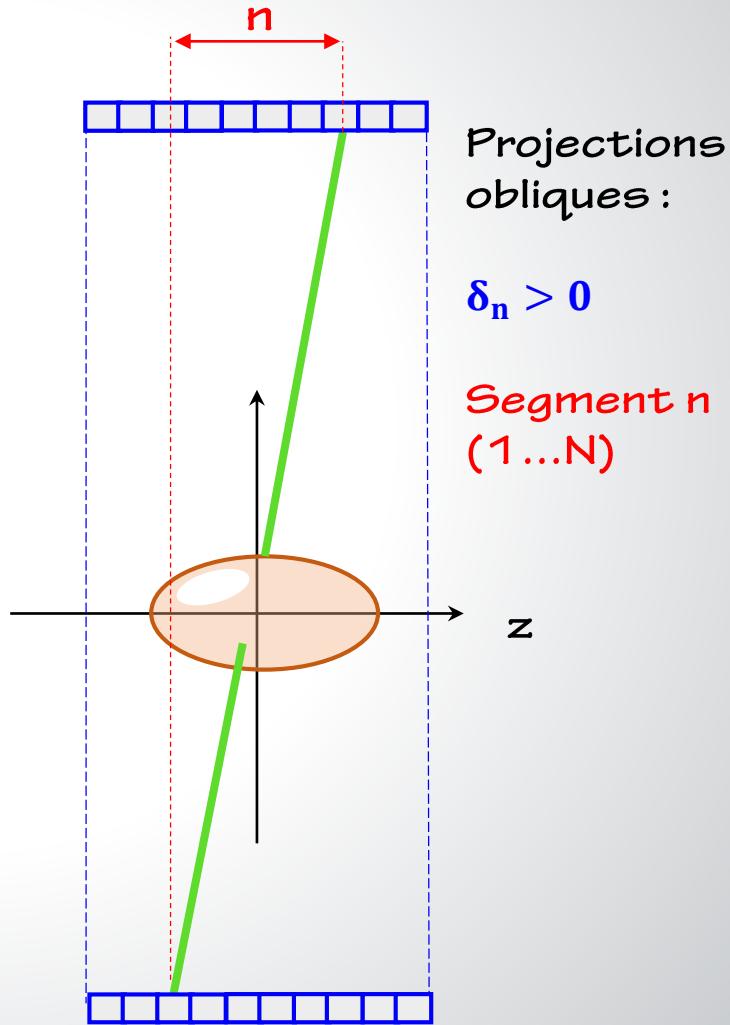
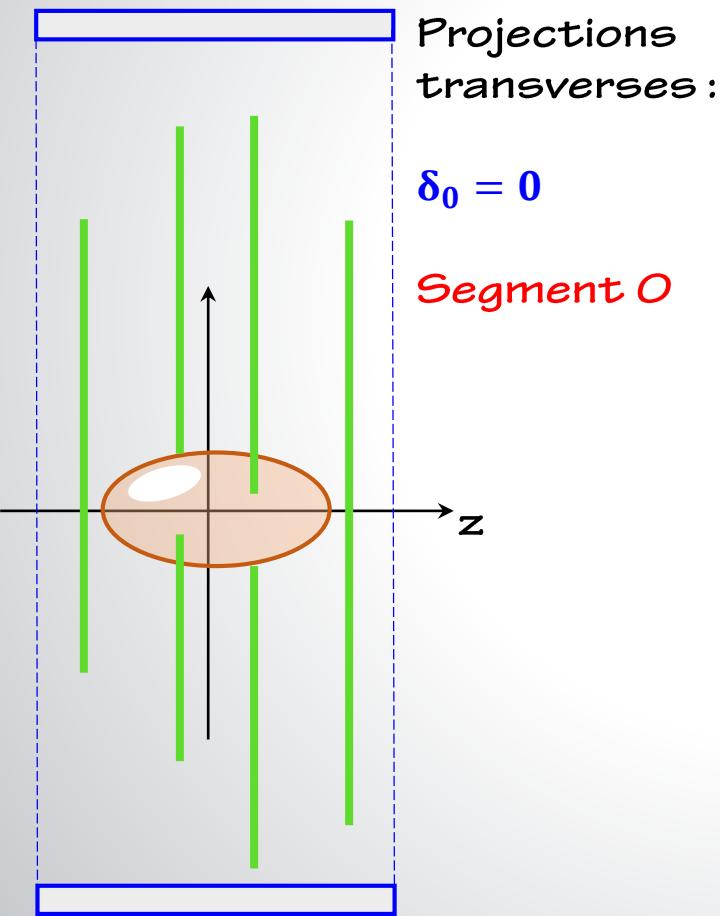
# TEP 3D

## ■ Encodage TEP



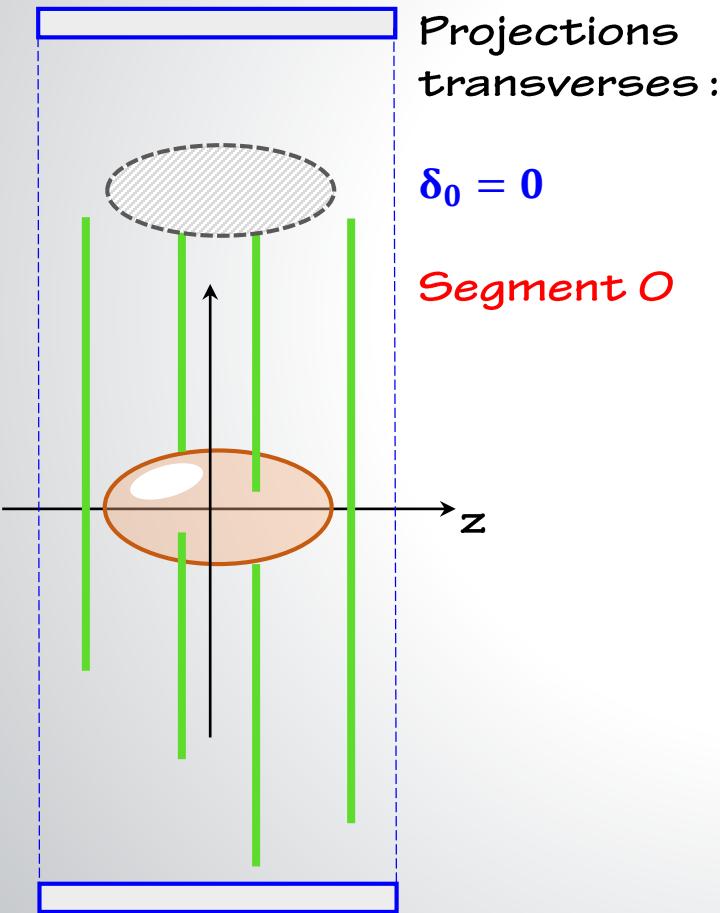
# TEP 3D

## ■ Encodage TEP



# TEP 3D

## ■ Encodage TEP



COMPLETEES  
&  
SUFFISANTES

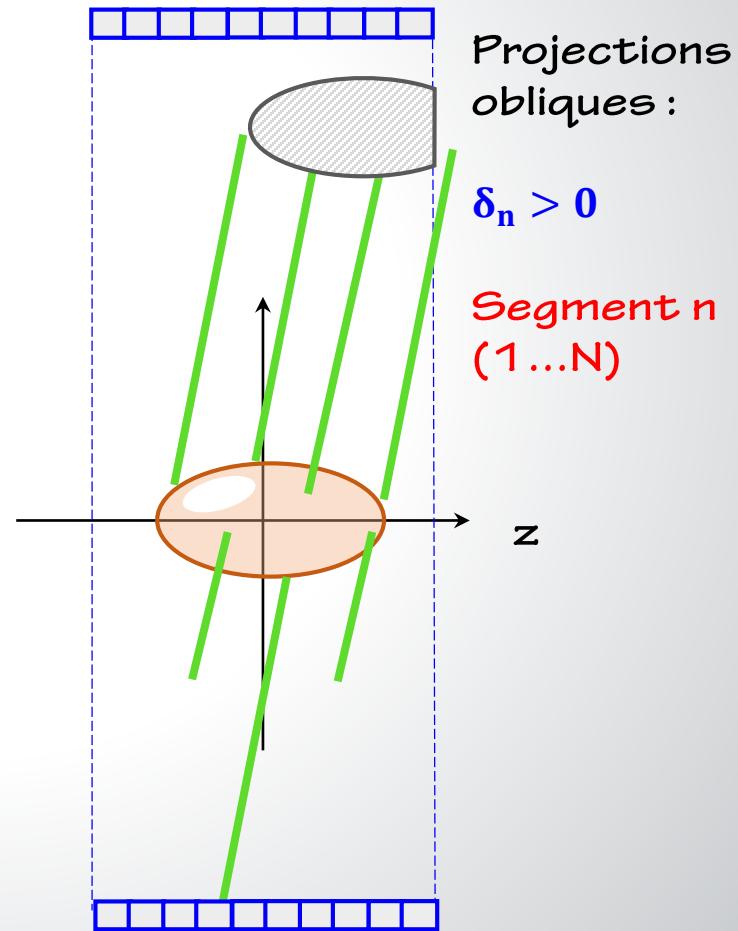
$$p(\mathbf{0}, z, \theta, s) \rightarrow f(x, y, z)$$

# TEP 3D

## ■ Encodage TEP

TRONQUEES

$$p(\delta_{n>0}, z, \theta, s) \rightarrow f(x, y, z)$$



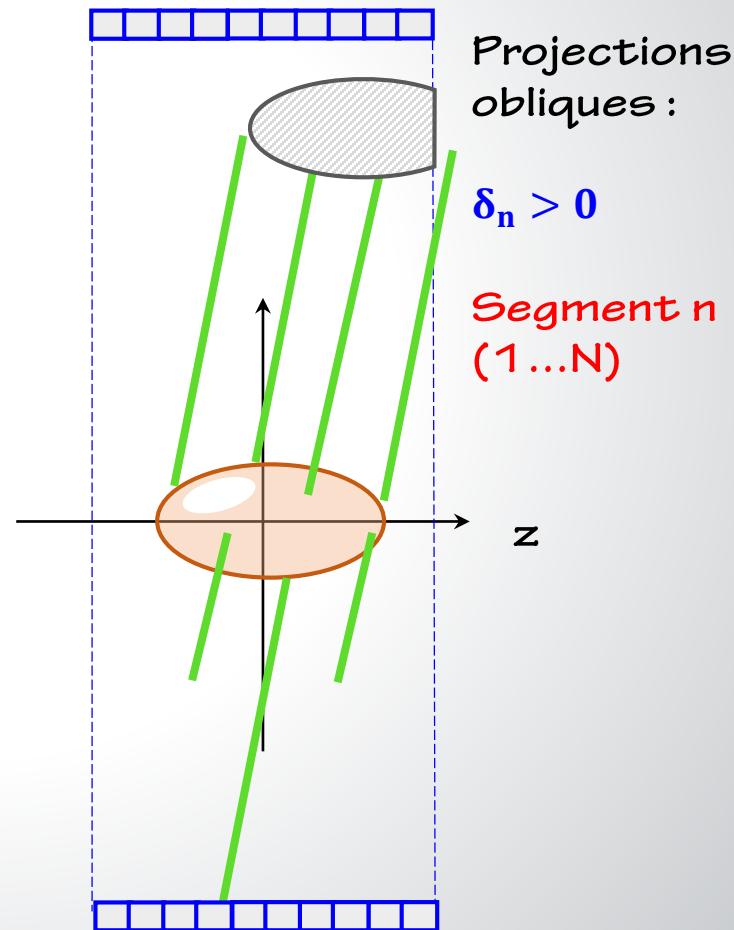
# TEP 3D

## ■ Encodage TEP

TRONQUEES  
&  
REDONDANTES

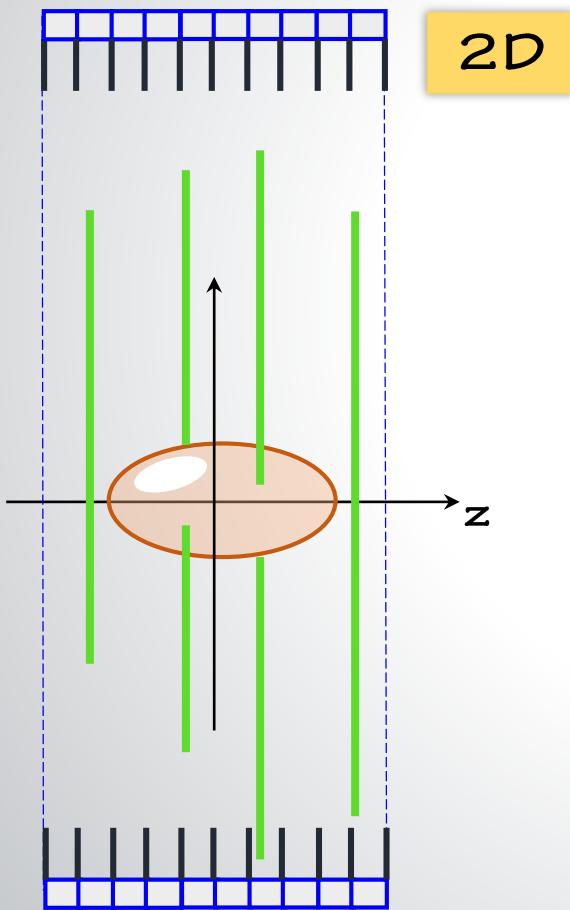
$$p(\delta_{n>0}, z, \theta, s) \rightarrow f(x, y, z)$$

$$\left. \begin{array}{l} p(0, z, \theta, s) \\ p(\delta_1, z, \theta, s) \\ p(\delta_2, z, \theta, s) \\ p(\delta_3, z, \theta, s) \\ \vdots \end{array} \right\} \rightarrow f(x, y, z)$$



# TEP 3D

## ■ Reconstruction



2D

$$p(0, z, \theta, s) \rightarrow f(x, y, z)$$

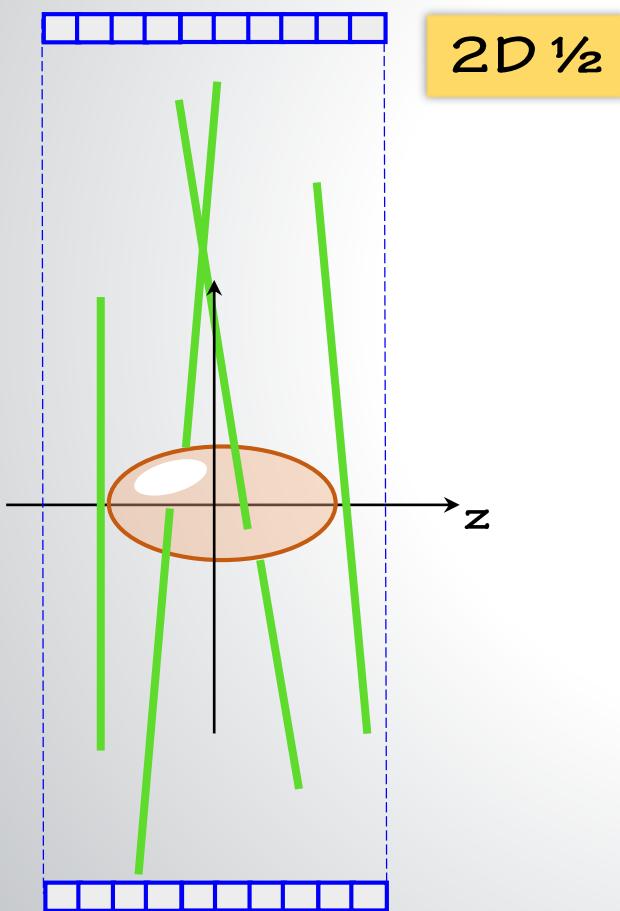
Collimation

Très rapide

SNR ↴

# TEP 3D

## ■ Reconstruction



$$p(0, z, \theta, s), p(\delta_1, z, \theta, s), p(\delta_2, z, \theta, s), \dots$$

↓

$$p(0, z, \theta, s)$$

↓

$$f(x, y, z)$$

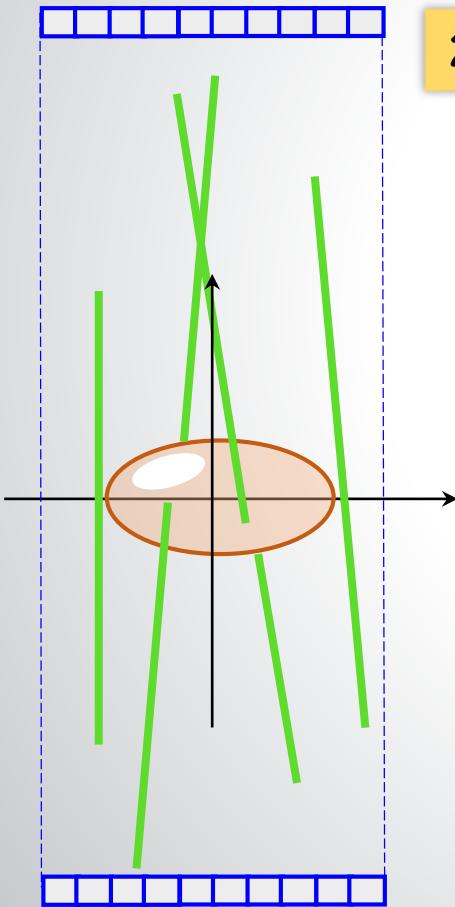
« Rebinning »

Rapide

Approximatif

# TEP 3D

## ■ Reconstruction



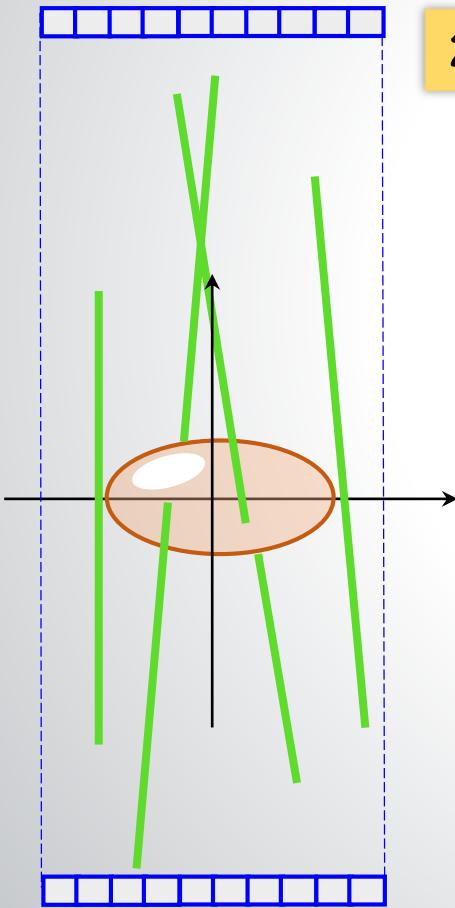
2D 1/2

REBINNING EXACT

$$\hat{p}(0, \zeta, k, \omega) = e^{-i k \operatorname{atan}(\frac{\delta\zeta}{\omega'})} \hat{p}(\delta, \zeta, k, \omega')$$
$$\omega' = \sqrt{\omega^2 - \delta^2 \zeta^2}$$

# TEP 3D

## ■ Reconstruction



2D 1/2

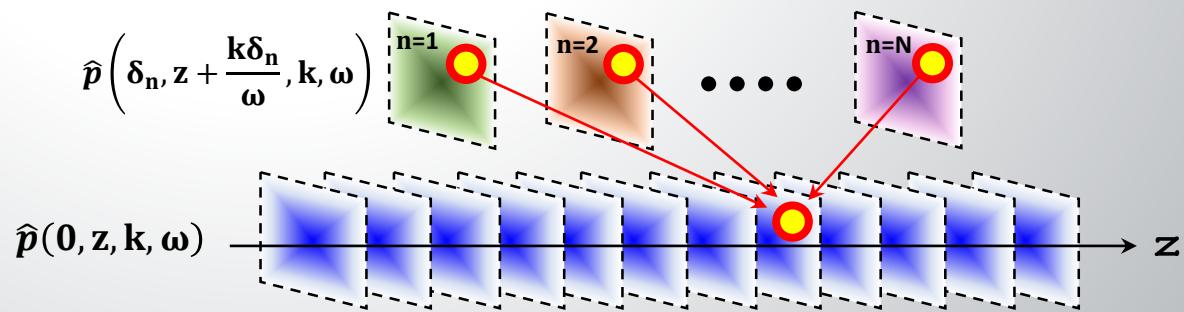
REBINNING EXACT

$$\hat{p}(0, \zeta, k, \omega) = e^{-i k \operatorname{atan}(\frac{\delta\zeta}{\omega'})} \hat{p}(\delta, \zeta, k, \omega')$$

$$\omega' = \sqrt{\omega^2 - \delta^2 \zeta^2}$$

REBINNING APPROXIMATION

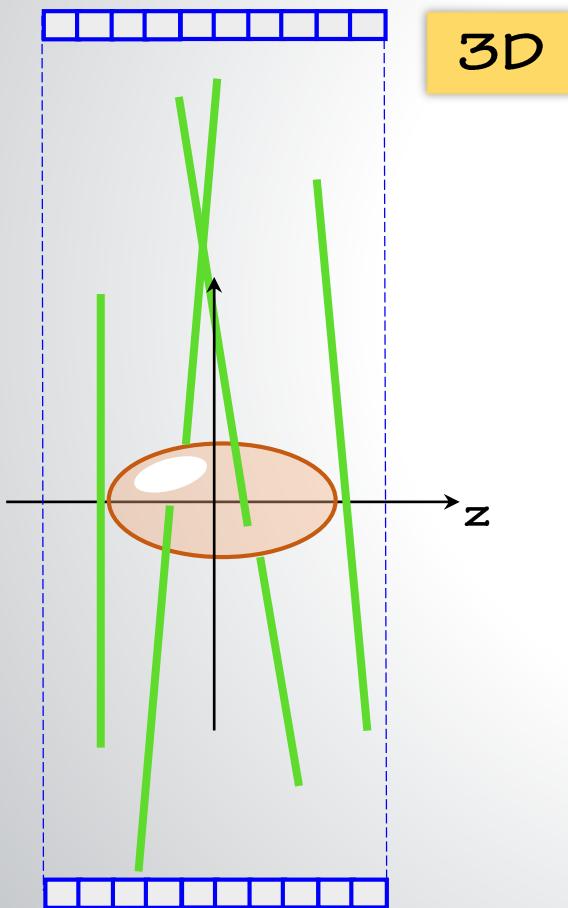
$$\hat{p}(0, z, k, \omega) = \hat{p}\left(\delta, z + \frac{k\delta}{\omega}, k, \omega\right)$$



$$\hat{p}(0, z, k, \omega)$$

# TEP 3D

## ■ Reconstruction



$$\left. \begin{array}{l} p(0, z, \theta, s) \\ p(\delta_1, z, \theta, s) \\ p(\delta_2, z, \theta, s) \\ p(\delta_3, z, \theta, s) \\ \vdots \end{array} \right\} \rightarrow f(x, y, z)$$

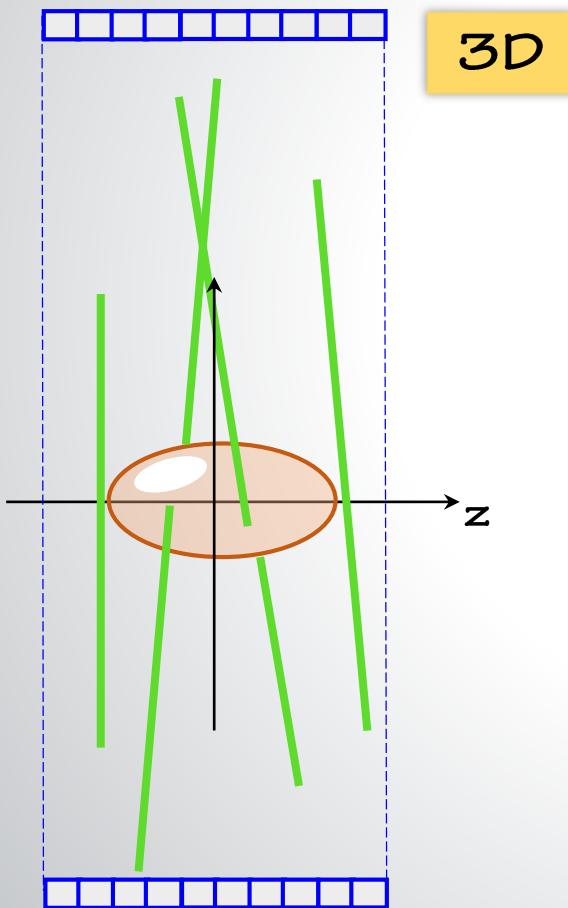
3D vrai

Reconstruction  
analytique ou itérative

SNR  $\uparrow$

# TEP 3D

## ■ Reconstruction



ALGEBRIQUE - ITERATIF

$$p(\delta, z, \theta, s) = R_{3D} f(x, y, z)$$

$$R_{3D} : \mathbb{R}^3 \rightarrow \mathbb{R}^2 \times C_1 \times \{0 \dots N\}$$

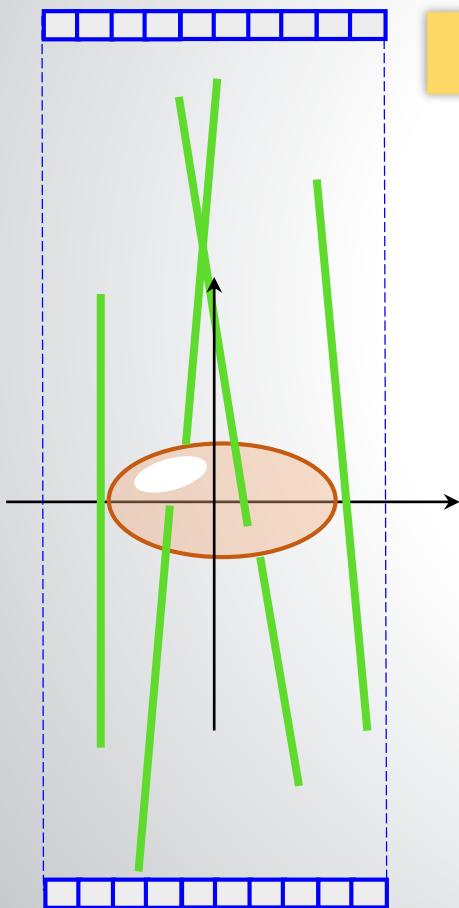
$$\text{Dim}(R_{3D}) >>$$

Stockage ?

Temps de calcul ...

# TEP 3D

## ■ Reconstruction



3D

ANALYTIQUE : Fourier ou RPF

!! Complémentation des données obliques !!

$$p(0, z, \theta, s) \rightarrow \tilde{f}(x, y, z)$$

$$\downarrow R\tilde{f}$$

$$\tilde{p}(\delta_{n>0}, z, \theta, s)$$

$$p(\delta_{n>0}, z, \theta, s)$$

Fusion

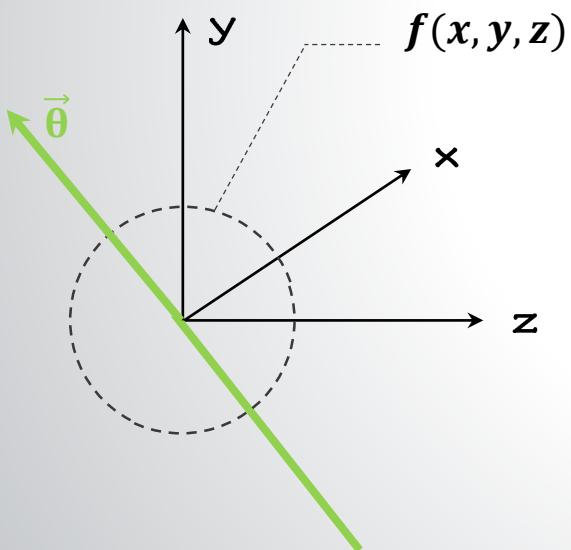
$$\left. \begin{array}{c} p(\delta_{n>0}, z, \theta, s) \\ p(0, z, \theta, s) \end{array} \right\} \rightarrow f(x, y, z)$$

# TEP 3D

## ■ Reconstruction

3D

Synthèse de Fourier 3D

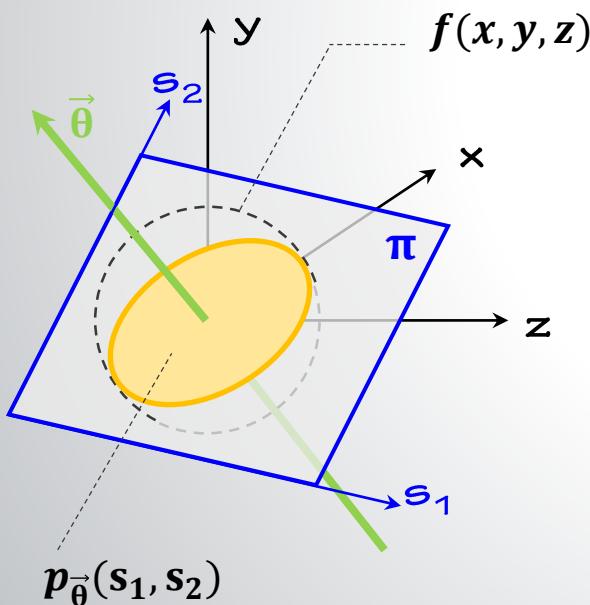


# TEP 3D

## ■ Reconstruction

3D

Synthèse de Fourier 3D

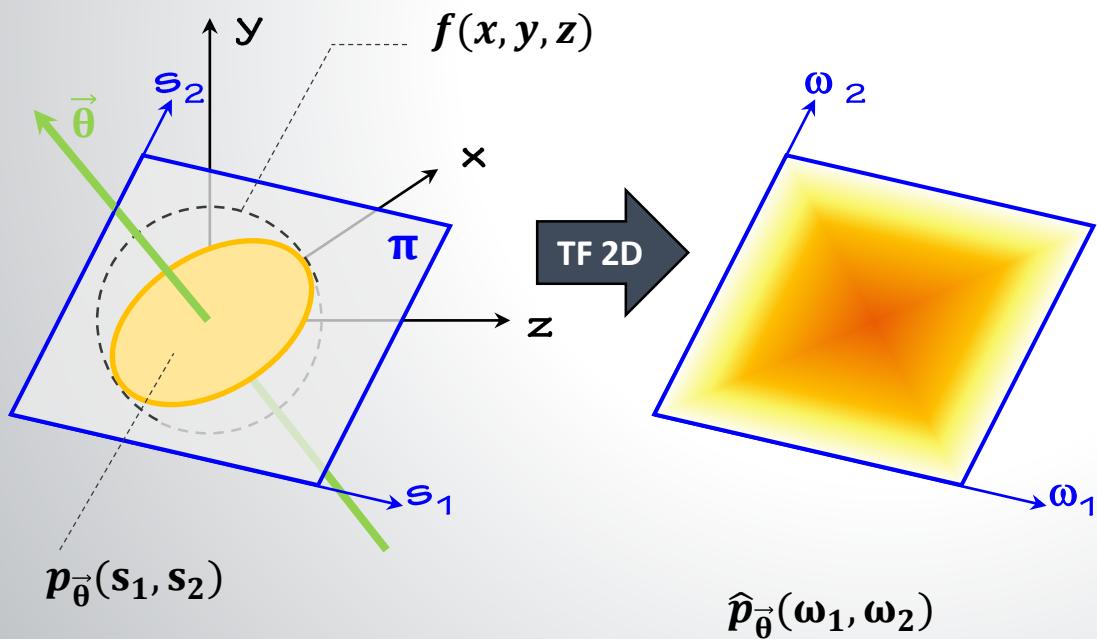


# TEP 3D

## ■ Reconstruction

3D

Synthèse de Fourier 3D



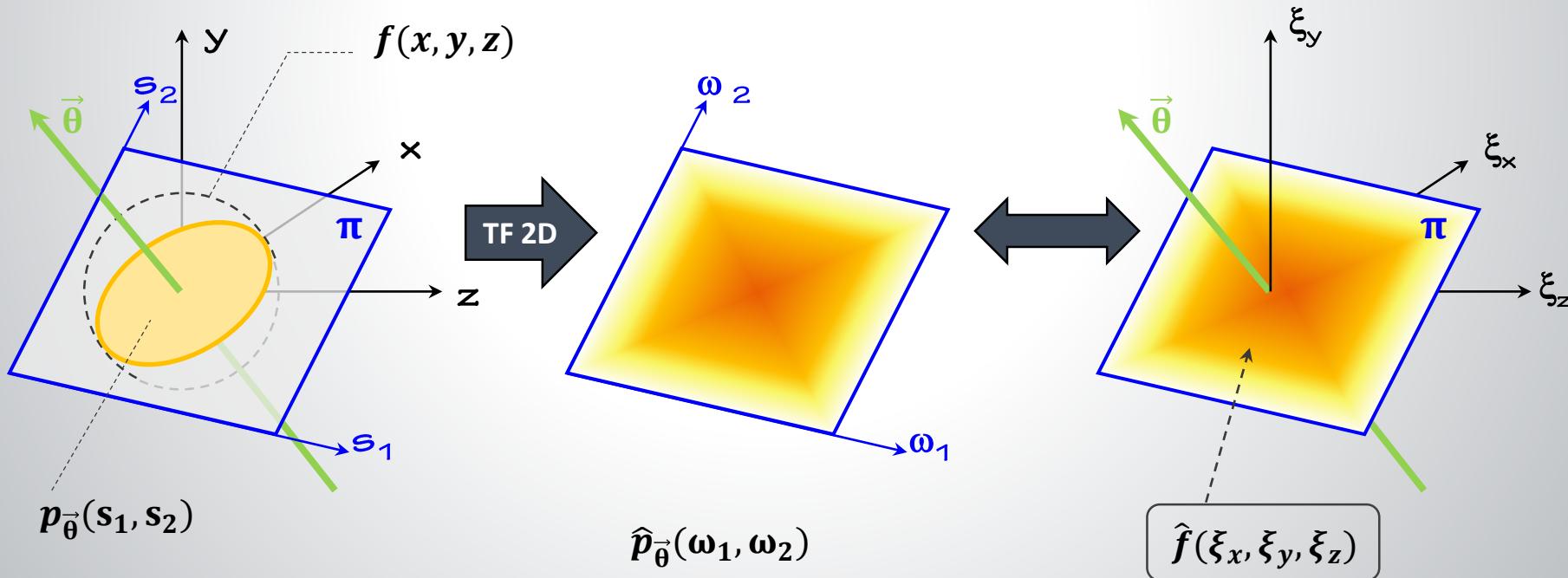
# TEP 3D

## ■ Reconstruction

3D

Synthèse de Fourier 3D

$$\hat{f}([\xi_x, \xi_y, \xi_z]) = R_{\vec{\theta}}[\omega_1, \omega_2] = \hat{p}_{\vec{\theta}}(\omega_1, \omega_2)$$



# TEP 3D

## ■ Reconstruction

3D

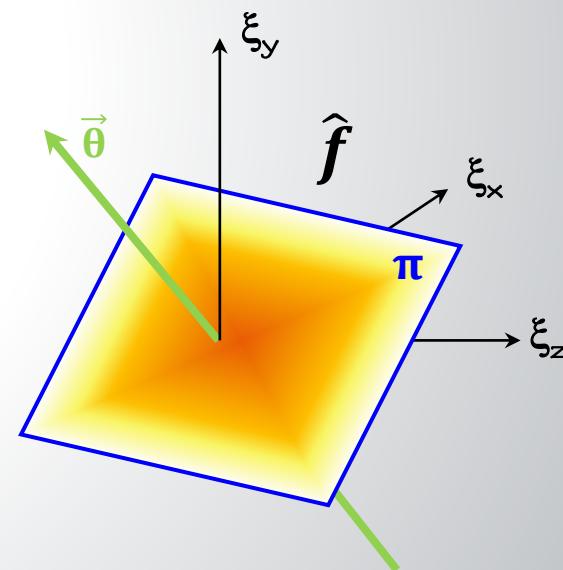
Synthèse de Fourier 3D

$$\hat{f}([\xi_x, \xi_y, \xi_z]) = R_{\vec{\theta}}[\omega_1, \omega_2] = \hat{p}_{\vec{\theta}}(\omega_1, \omega_2)$$

Condition d'ORLOV

Nécessaire et suffisante pour que  $\pi$  décrive  $\mathbb{R}^3$

$$\begin{aligned}\vec{\theta} &\in \Omega \subset S^2 \\ \exists C &\in S^2 : C \subset \Omega \\ \forall C &\in S^2 : \Omega \cap C \neq \emptyset\end{aligned}$$



# TEP 3D

## ■ Reconstruction

3D

Synthèse de Fourier 3D

$$\hat{f}([\xi_x, \xi_y, \xi_z]) = R_{\vec{\theta}}[\omega_1, \omega_2] = \hat{p}_{\vec{\theta}}(\omega_1, \omega_2)$$

Condition d'ORLOV

Nécessaire et suffisante pour que  $\pi$  décrive  $\mathbb{R}^3$

$$\begin{aligned}\vec{\theta} &\in \Omega \subset S^2 \\ \exists C &\in S^2 : C \subset \Omega \\ \forall C &\in S^2 : \Omega \cap C \neq \emptyset\end{aligned}$$

