

TRAITEMENT NUMERIQUE DES IMAGES MEDICALES (I)

**NUMERISATION
FILTRAGE
SEGMENTATION**

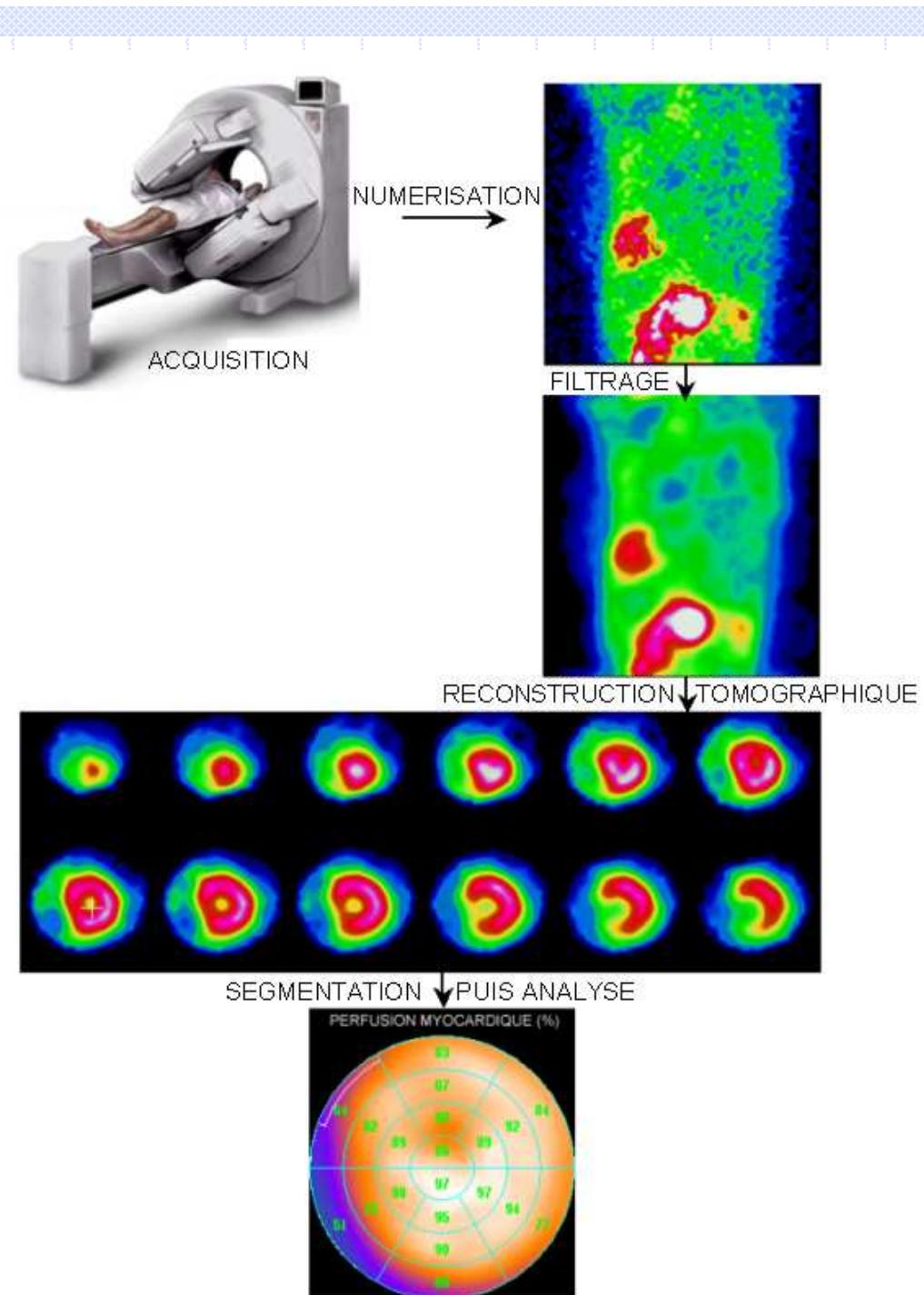
D. MARIANO-GOULART

PLAN

- ◆ **Images analogiques & numériques**
- ◆ Transformée de Fourier discrète
- ◆ Formation de l'image, résolution
- ◆ Théorème d'échantillonnage
- ◆ Filtrage linéaire
- ◆ Filtrage non linéaire

① Notion d'image

CHAINE
D'ACQUISITION,
DE TRAITEMENT,
DE RECONSTRUCTION
ET D'ANALYSE
D'IMAGE



① Notion d'image

Notion d'image

$s(x,y)$

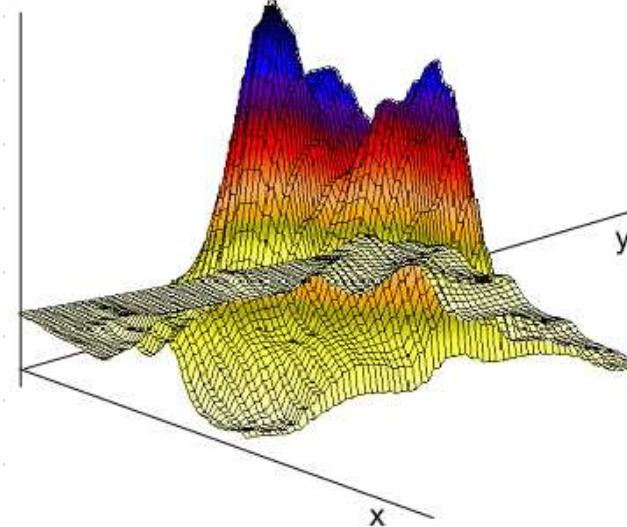
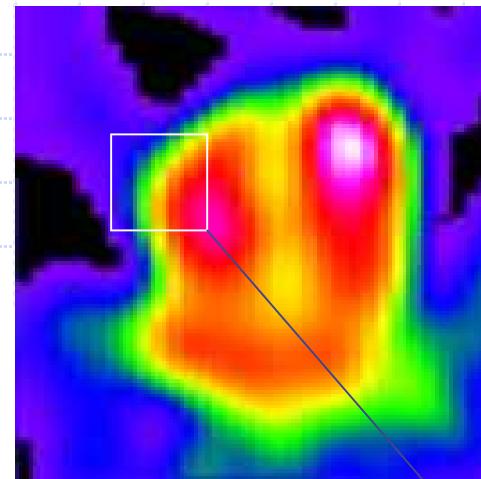


IMAGE ANALOGIQUE



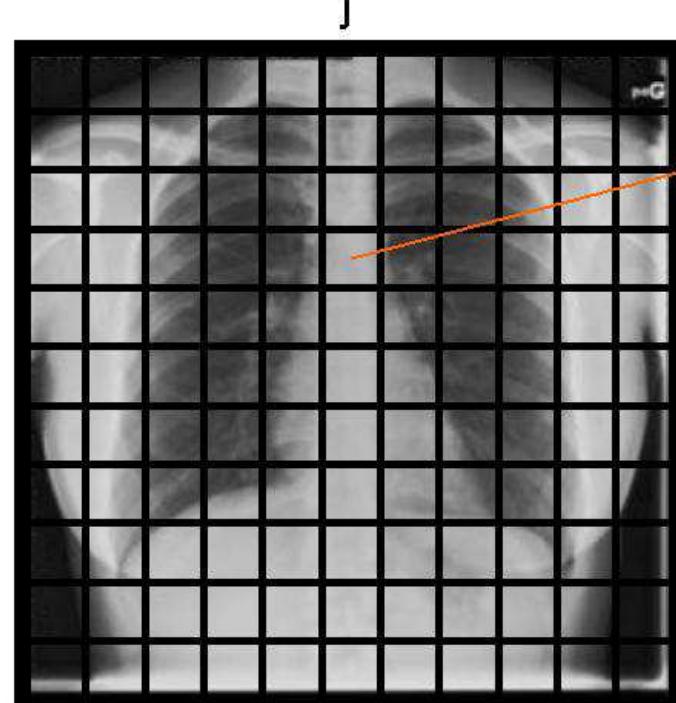
MESURE D'UN
SIGNAL PHYSIQUE
2D

10	12	15	15	13	15	23	24
9	15	19	18	15	16	22	25
5	16	25	22	18	18	22	29
4	15	28	32	23	21	25	32
2	7	21	23	25	22	22	25
1	5	15	21	22	21	19	19
2	6	13	16	18	18	18	18
9	9	10	15	16	15	16	16

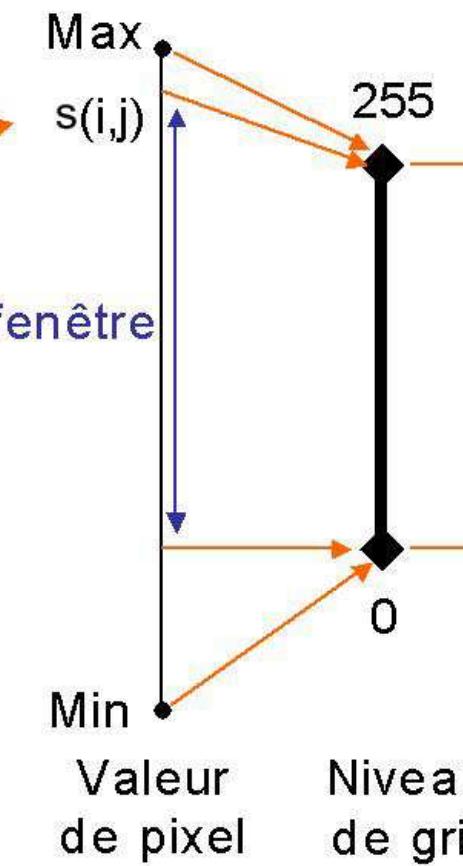
IMAGE NUMERIQUE

① Notion d'image

Numérisation



Pixels



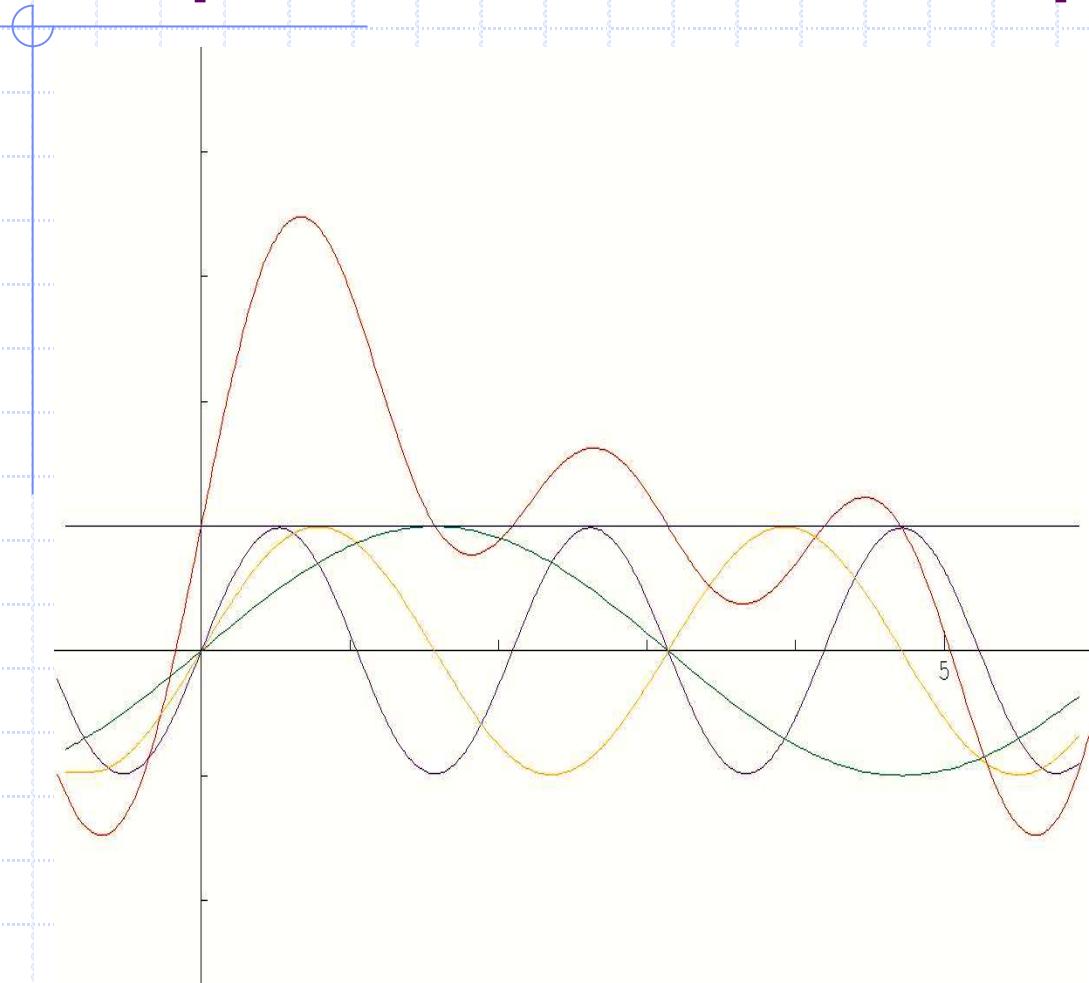
② TFD

REPRESENTATION EN FREQUENCES

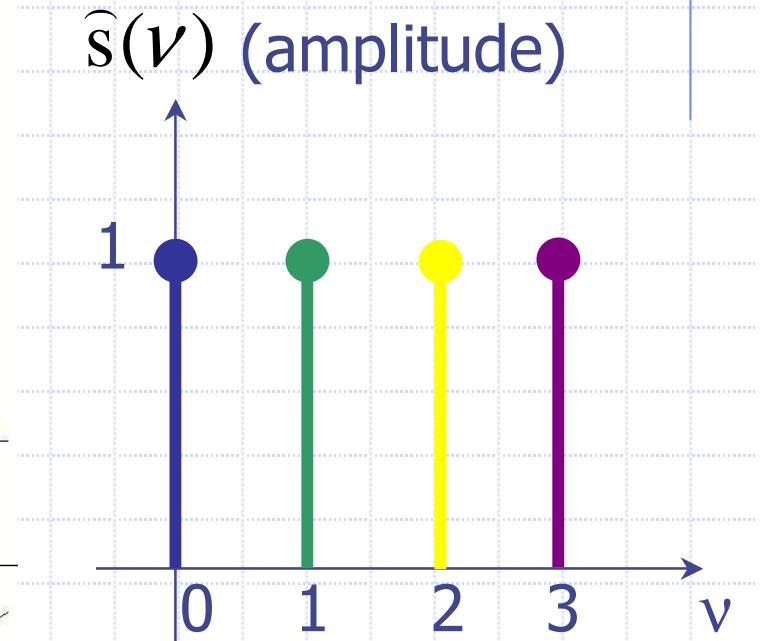
TRANSFORMATION DE FOURIER

② TFD

Représentation fréquentielle

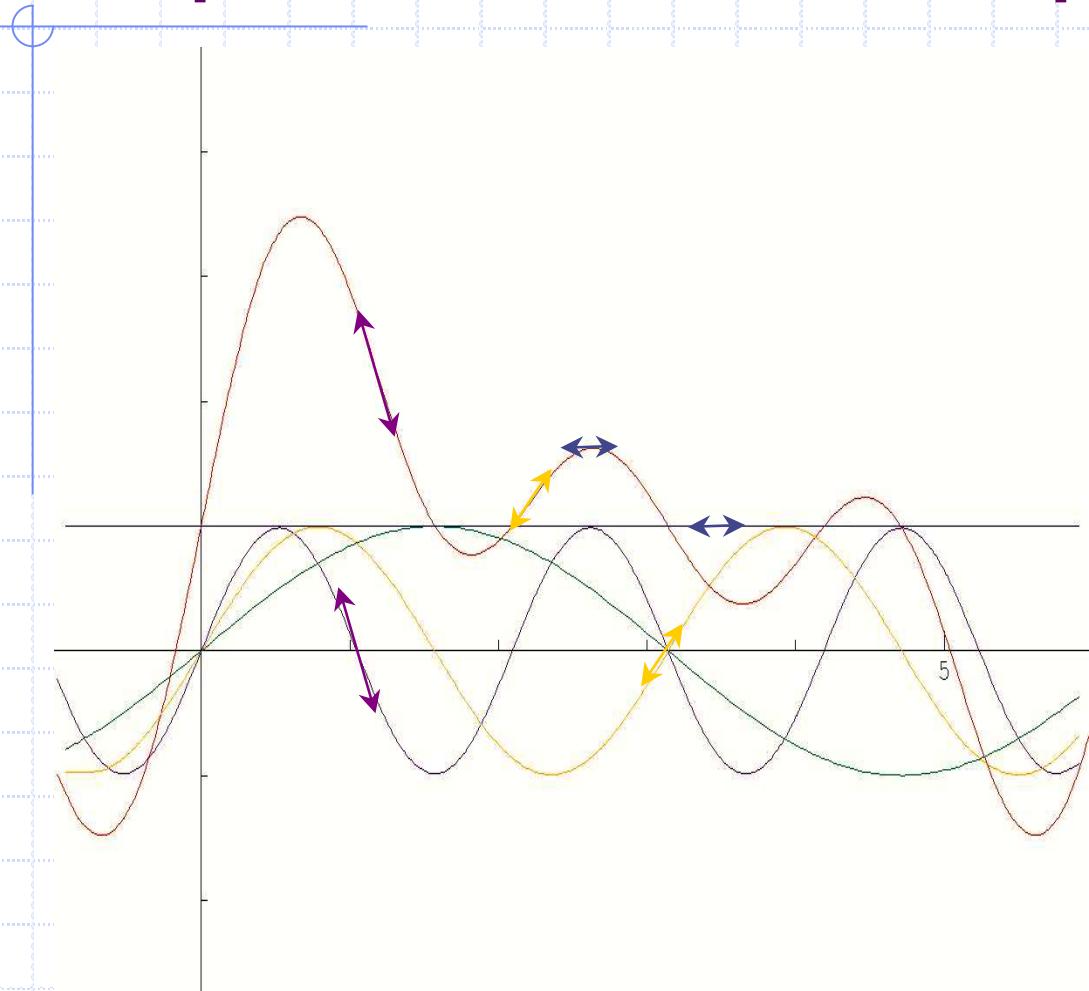


$\hat{s}(\nu)$ (amplitude)

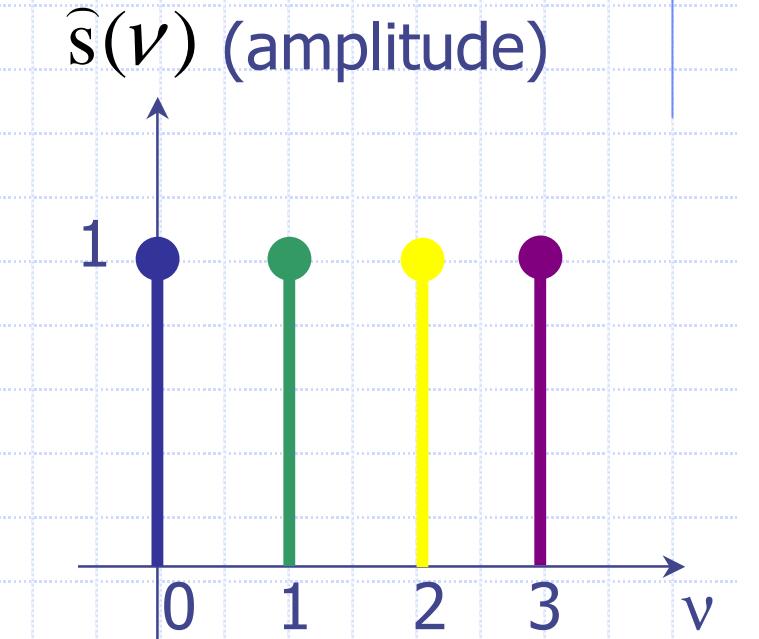


② TFD

Représentation fréquentielle

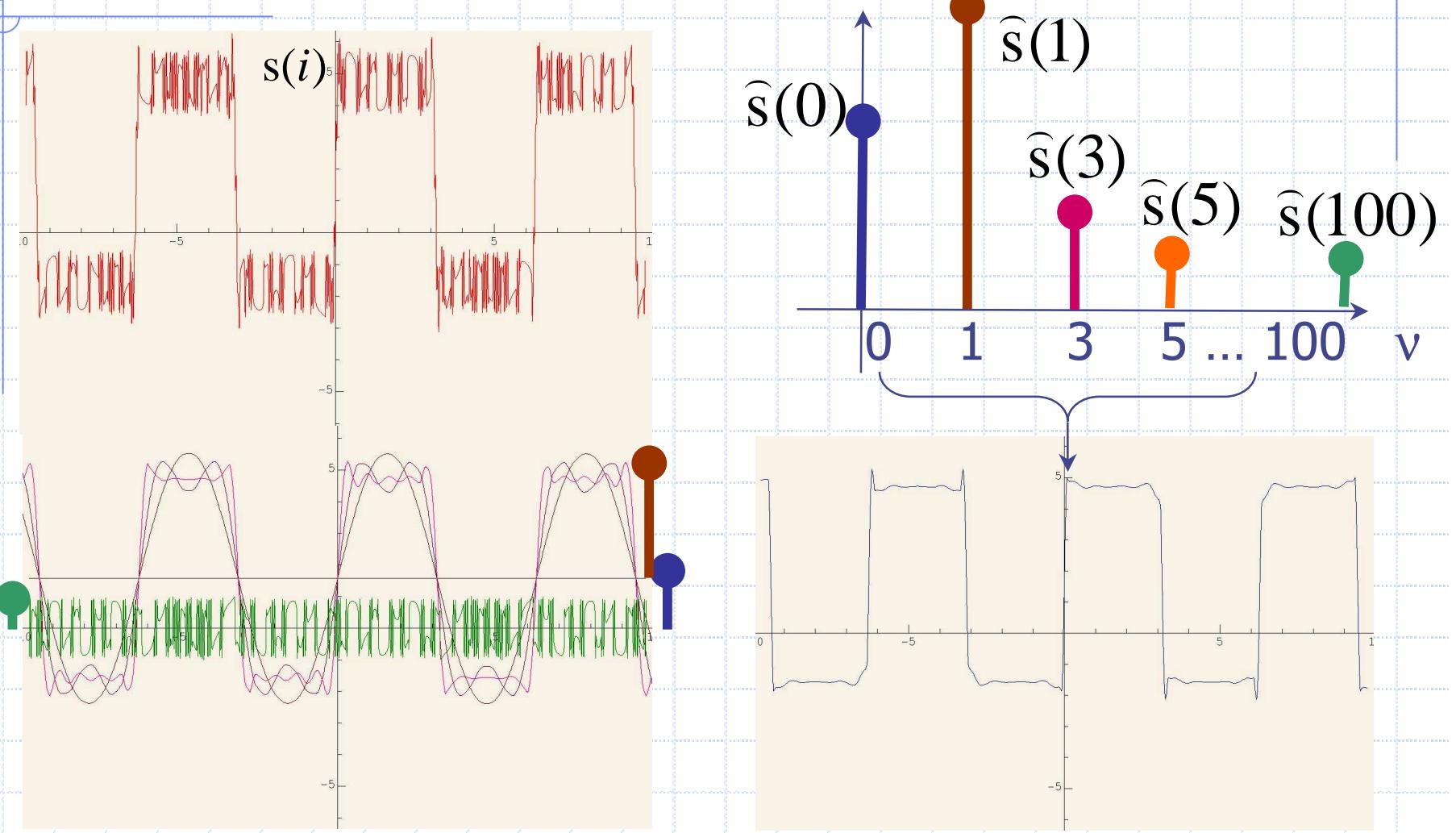


$\hat{s}(\nu)$ (amplitude)



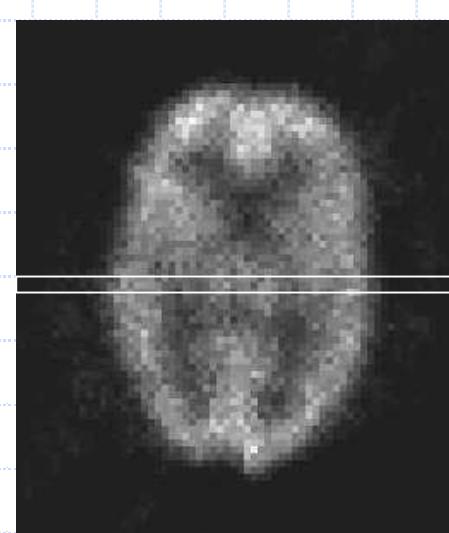
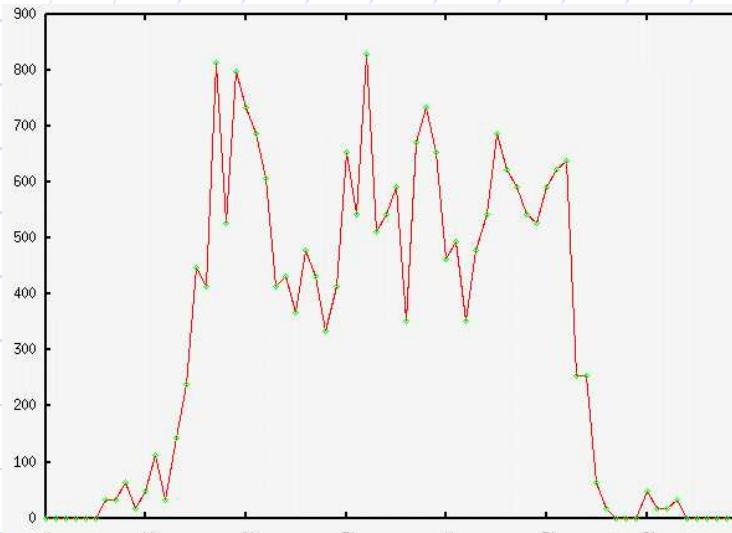
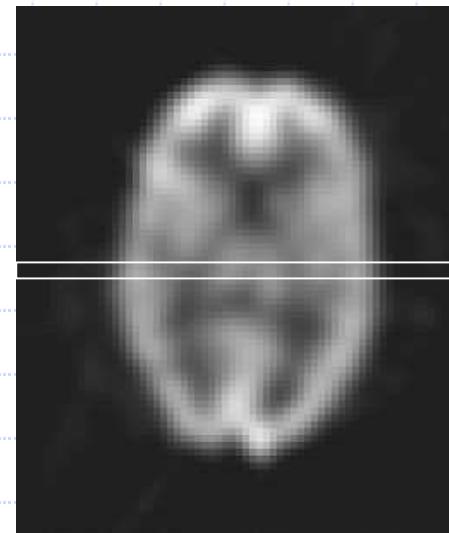
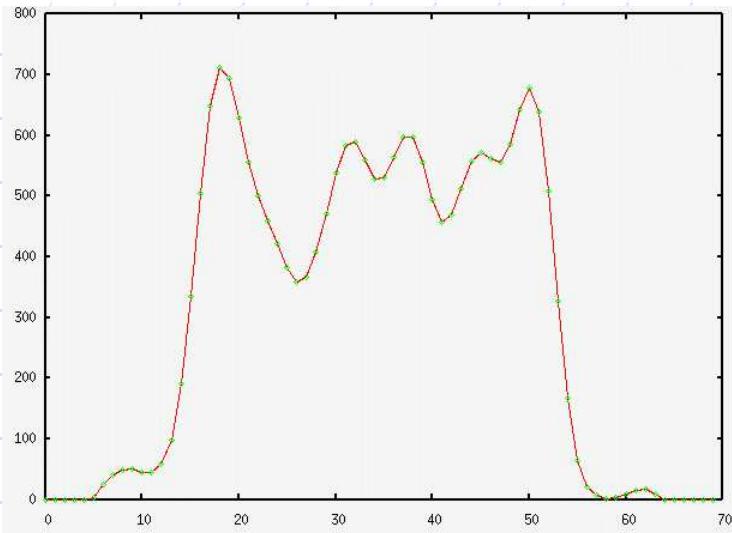
② TFD

Représentation fréquentielle



② TFD

Représentation fréquentielle



② TFD

C'est un peu plus compliqué...

$$s(t) = A_0 + \sum_{k=1}^{\infty} A_k \cos[(k\omega)t + \phi_k]$$

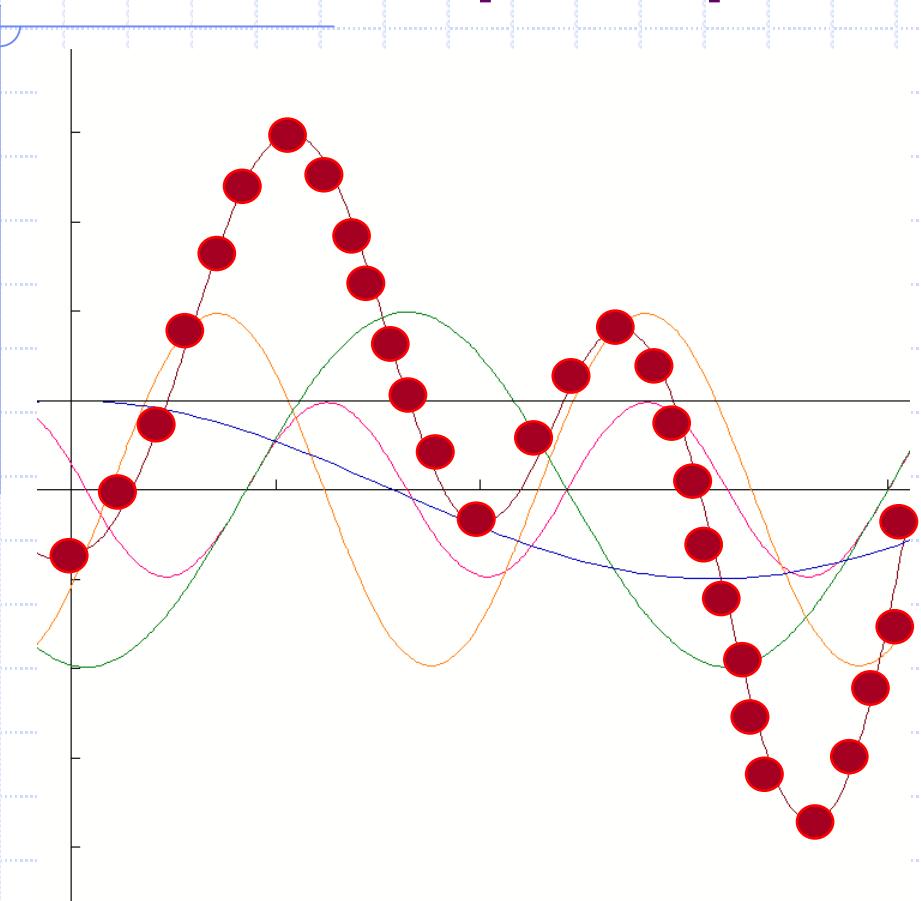
∞

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$$s(t) = A_0 + \sum_{k=1}^{\infty} A_k \cos[(k\omega)t + \phi_k]$$

② TFD

C'est un peu plus compliqué...

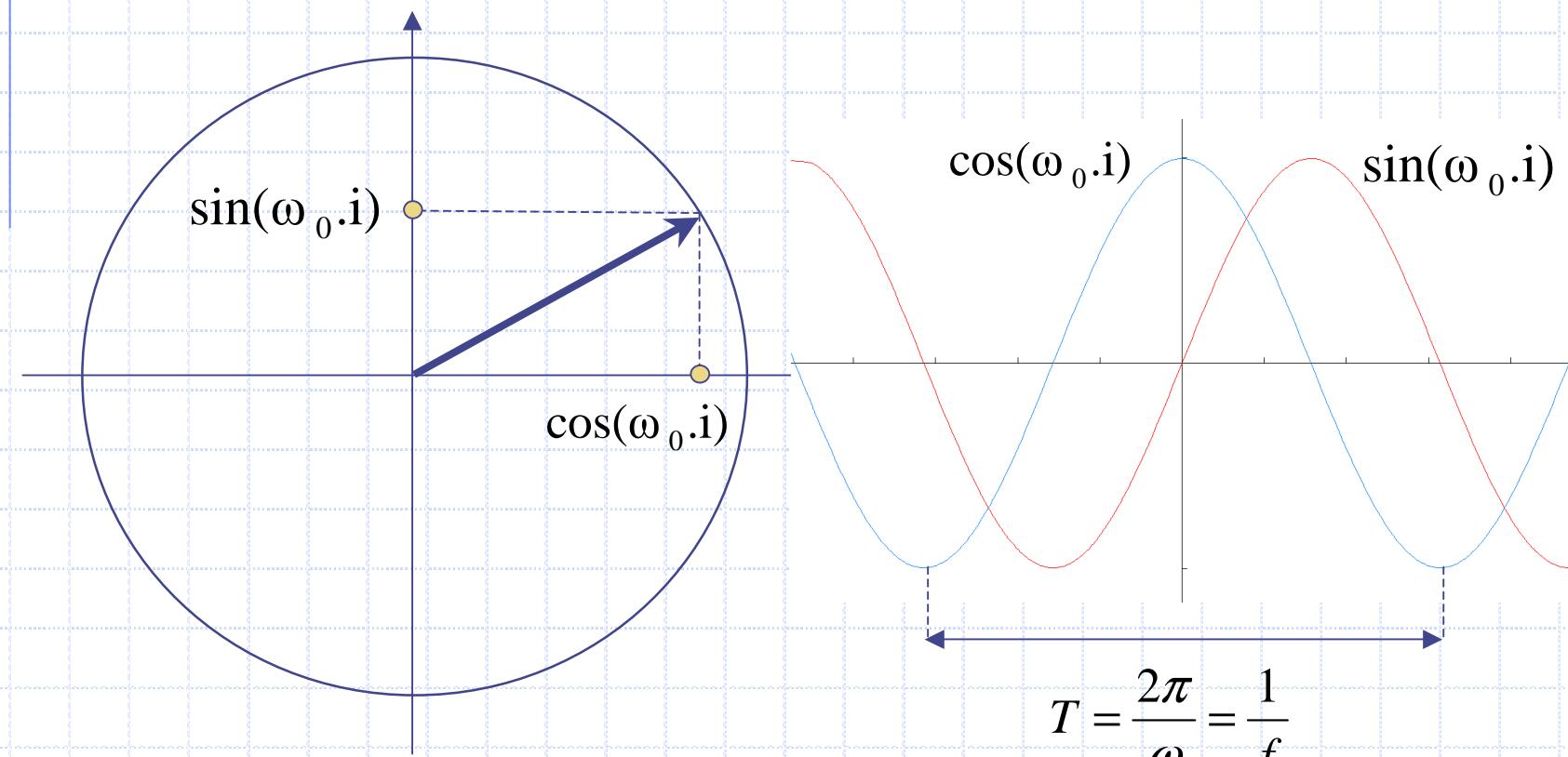


$$A_k \cos[\varphi_k] \cos[(k\omega)t] - A_k \sin[\varphi_k] \sin[(k\omega)t]$$

$$s(t) = A_0 + \sum_{k=1}^{\infty} A_k \cos[(k\omega)t + \varphi_k]$$

Rappel: nombres complexes

$$f(i) = e^{j \cdot \omega_0 \cdot i} = \cos(\omega_0 \cdot i) + j \cdot \sin(\omega_0 \cdot i)$$



Transformée de Fourier discrète

$$s(i) = \frac{1}{N} \sum_{k=0}^{N-1} \hat{s}(k) \cdot e^{j \cdot (k \cdot \omega_0) i}$$

$$\omega_0 = 2\pi \frac{1}{N} \text{ fondamentale}$$

$$s(i) = \frac{1}{N} [$$

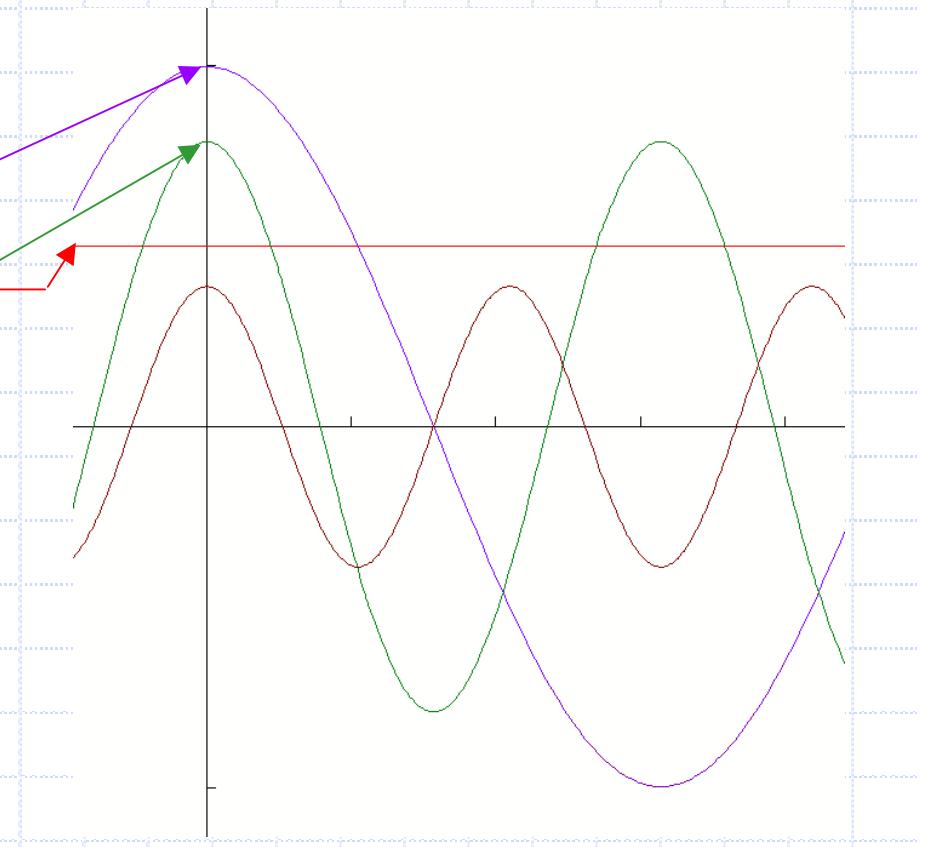
$\hat{s}(0)$

$+ \hat{s}(1) \cdot e^{j \cdot (\omega_0) i}$

$+ \hat{s}(2) \cdot e^{j \cdot (2 \cdot \omega_0) i} + \dots$

$+ \hat{s}(N-1) \cdot e^{j \cdot ((N-1) \cdot \omega_0) i}$

]



Transformée de Fourier discrète

$$s(i) = \frac{1}{N} \sum_{k=0}^{N-1} \hat{s}(k) \cdot e^{j \cdot (k \frac{2\pi}{N}) i}$$

$$\hat{s}(\nu) = \sum_{k=0}^{N-1} s(k) \cdot e^{-j \cdot (k \frac{2\pi}{N}) \nu} = A_\nu e^{j \phi_\nu}$$

Transformée de Fourier discrète

$$s(i) = \frac{1}{N} \sum_{k=0}^{N-1} \hat{s}(k) \cdot e^{j \cdot (k \frac{2\pi}{N}) i}$$

$$\hat{s}(\nu) = \sum_{k=0}^{N-1} s(k) \cdot e^{-j \cdot (k \frac{2\pi}{N}) \nu}$$

$$s(i) = ? \sum_{k=0}^{N-1} \left[\sum_{k'=0}^{N-1} s(k') \cdot e^{-j \cdot (k' \frac{2\pi}{N}) k} \right] \cdot e^{j \cdot (k \frac{2\pi}{N}) i}$$

$$s(i) = ? \sum_{k'=0}^{N-1} s(k') \left[\sum_{k=0}^{N-1} \cdot e^{k \cdot (j \frac{2\pi}{N}) (i-k')} \right]$$

$$k' \neq i \Rightarrow \sum_{k=0}^{N-1} \cdot e^{k \cdot (j \frac{2\pi}{N}) (i-k')} = \frac{1 - e^{j \cdot 2\pi (i-k')}}{1 - e^{j \frac{2\pi}{N} (i-k')}} = 0,$$

$$k' = i \Rightarrow \sum_{k=0}^{N-1} \cdot e^{k \cdot (j \frac{2\pi}{N}) (i-k')} = N$$

② TFD

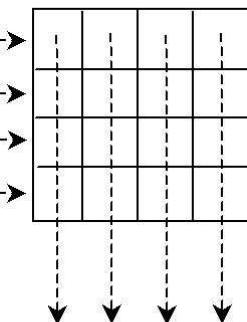
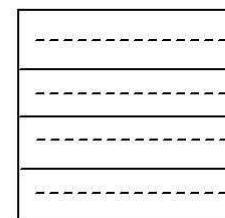
TF discrète 2D

$$s(i, j) = \frac{1}{N^2} \sum_{k=0}^{N-1} \sum_{k'=0}^{N-1} \hat{s}(k, k') e^{j \cdot [ki + k'j] \omega_0}$$

$$\hat{s}(v, v') = \sum_{k=0}^{N-1} \sum_{k'=0}^{N-1} s(k, k') e^{-j \cdot [kv + k'v'] \omega_0}$$

TF 1D des lignes

$$s(i, j) \longrightarrow s(i, v')$$

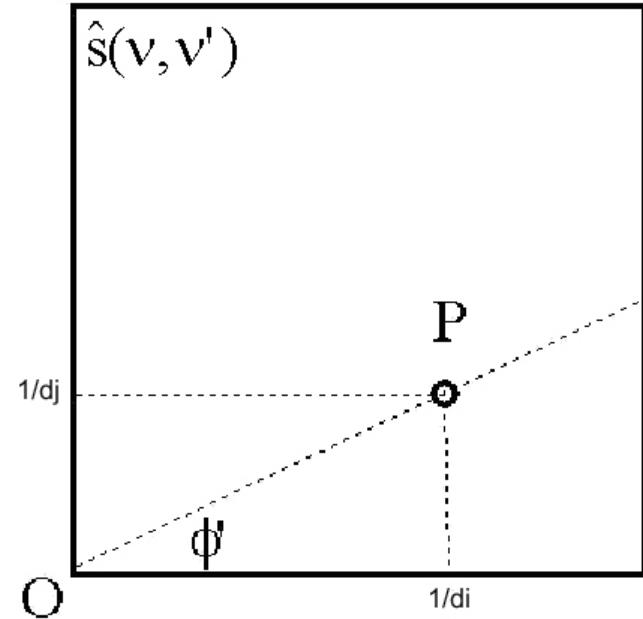
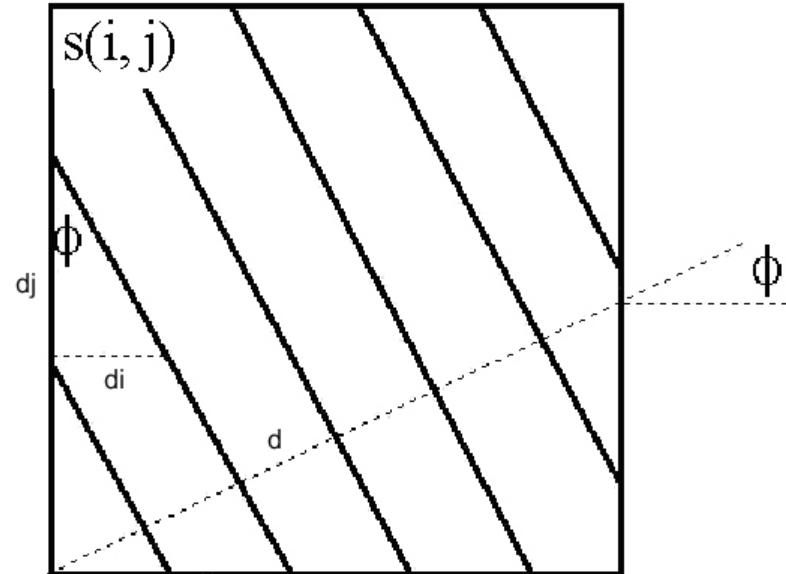


TF 1D des colonnes

$$\hat{s}(v, v')$$

② TFD

TF discrète 2D: interprétation



$$\tan \phi = \frac{d_i}{d_j}$$

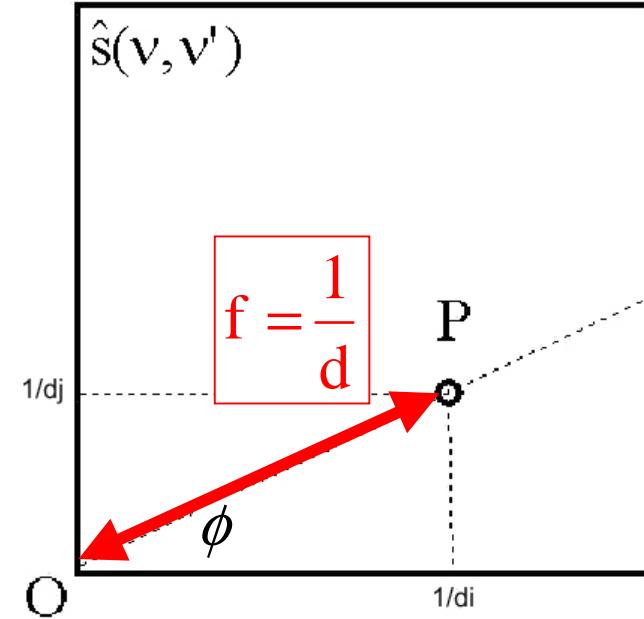
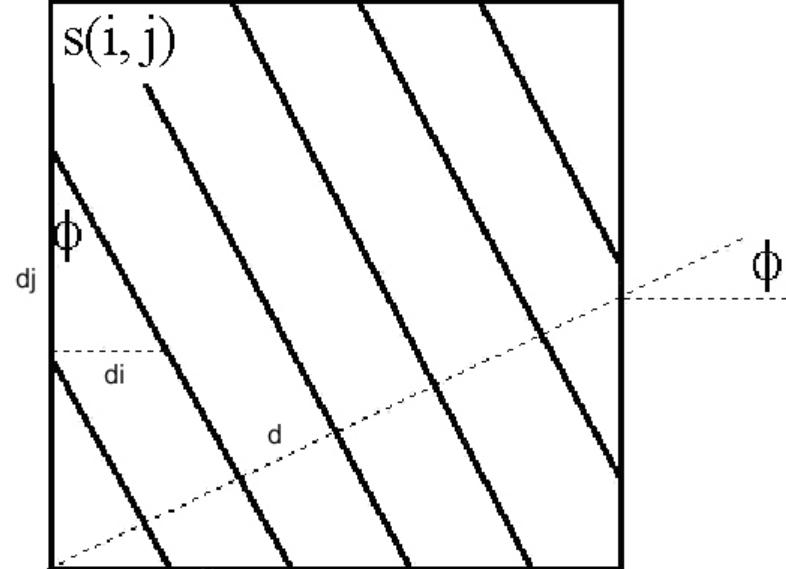
$$\cos \phi = \frac{d}{d_i}$$

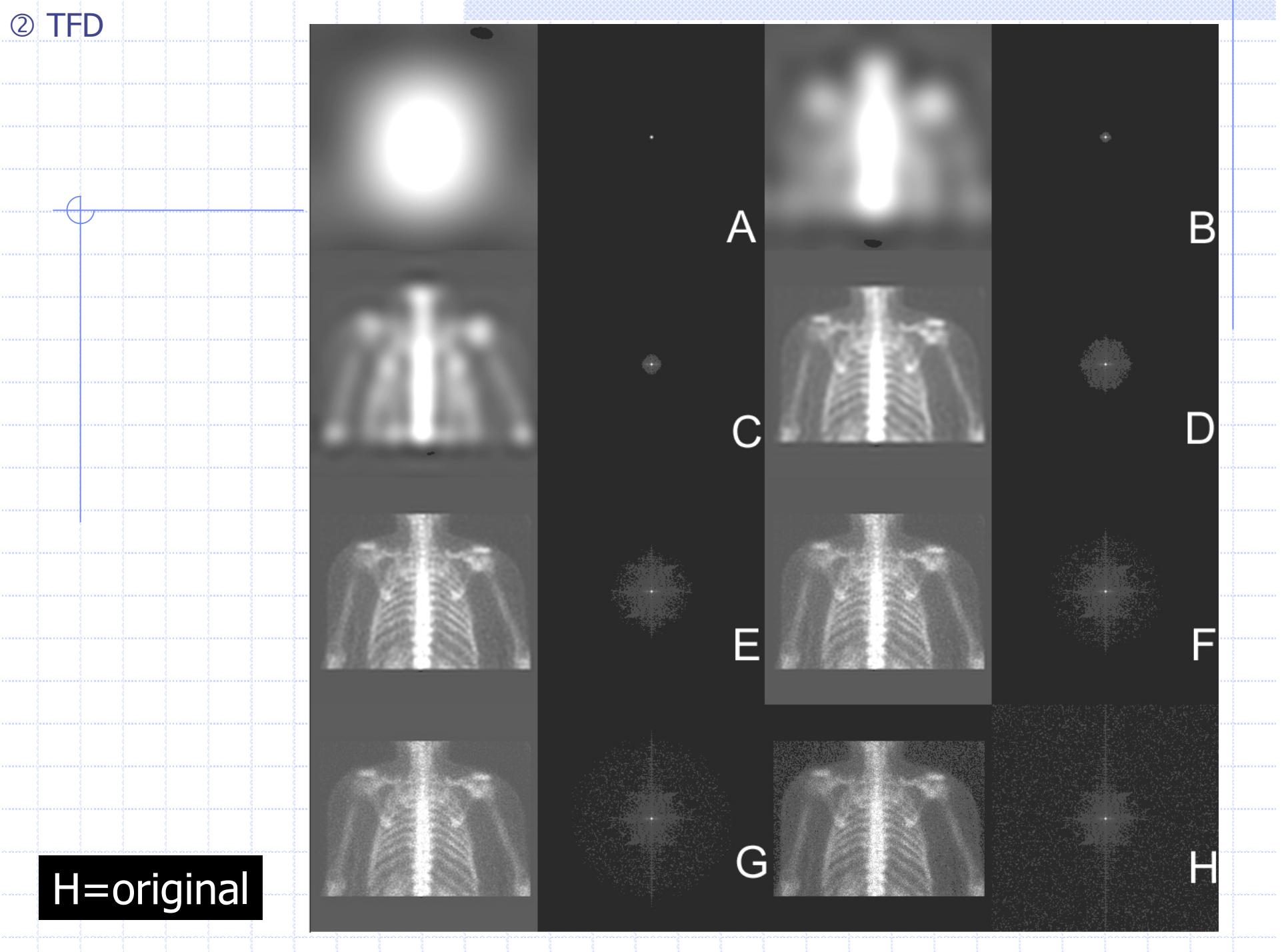
$$\tan \phi' = \frac{1/d_j}{1/d_i} \Rightarrow \phi' = \phi$$

$$\cos \phi = \frac{1/d_i}{OP} \Rightarrow OP = \frac{1}{d}$$

② TFD

TF discrète 2D: interprétation





Fast Fourier Transform (FFT)

$$\hat{s}(v) = \sum_{k=0}^{N-1} s(k) \cdot e^{-j \cdot (k\omega_0)v} = \sum_{k=0}^{N-1} s(k) \cdot W_N^{kv}$$

$$W_N = e^{-j \cdot \frac{2\pi}{N}} = e^{-j \cdot \omega_0}$$

$$W_N = \cos\left(\frac{2\pi}{N}\right) - j \cdot \sin\left(\frac{2\pi}{N}\right)$$

$$\begin{aligned} \hat{s}(v) &= \sum_{k=0}^{\frac{N}{2}-1} s(2k) \cdot W_N^{2k \cdot v} + \sum_{k=0}^{\frac{N}{2}-1} s(2k+1) \cdot W_N^{(2k+1) \cdot v} \\ &= \sum_{k=0}^{\frac{N}{2}-1} s(2k) \cdot W_N^{2k \cdot v} + W_N^v \sum_{k=0}^{\frac{N}{2}-1} s(2k+1) \cdot W_N^{2k \cdot v} \\ &= \sum_{k=0}^{\frac{N}{2}-1} s(2k) \cdot W_{N/2}^{k \cdot v} + W_N^v \sum_{k=0}^{\frac{N}{2}-1} s(2k+1) \cdot W_{N/2}^{k \cdot v} \\ &= G(v) + W_N^v \cdot H(v) \end{aligned}$$

Fast Fourier Transform (FFT)

TF sur N points

TF sur N/2 points

$$\hat{s}(\nu) = G(\nu) + W_N^\nu \cdot H(\nu)$$

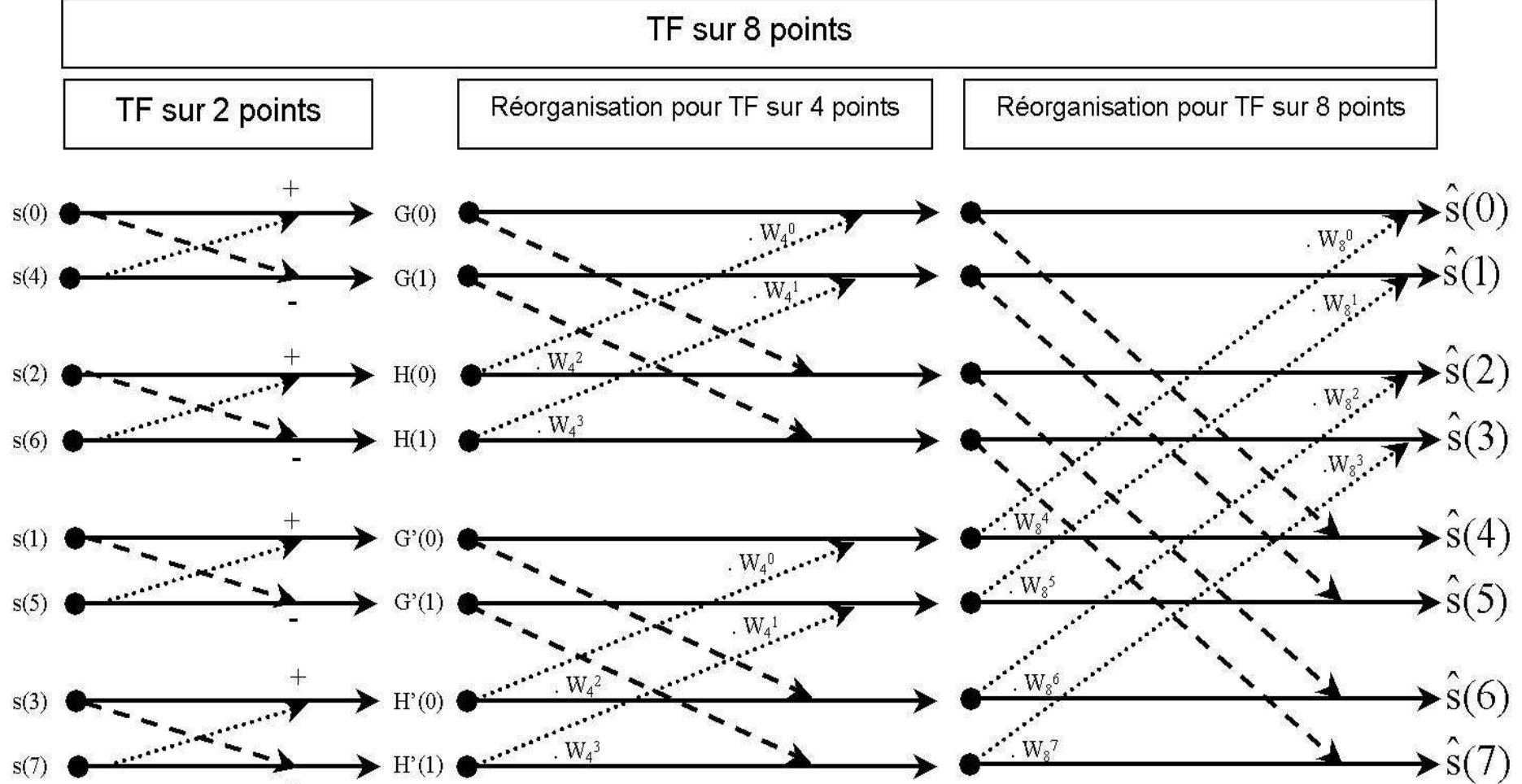
$$\cos\left(\frac{2\pi\nu}{N}\right) - j \cdot \sin\left(\frac{2\pi\nu}{N}\right)$$

TF sur 2 points: $\hat{s}(\nu) = \sum_{k=0}^1 s(k) \cdot e^{-j \cdot (k \frac{2\pi}{2})\nu} = s(0) + (-1)^\nu s(1)$

Complexité $N^2 \rightarrow N \cdot \log_2 N$ ($512^2 \rightarrow 512 \times 9$ i.e. 57 fois moins)

② TFD

Algorithme FFT



Autres décompositions de Fourier

Série de Fourier
 $f(x)$ périodique

$$f(x) = \frac{1}{T} \sum_{k \in \mathbb{Z}} \hat{f}(k) \cdot e^{j \cdot (k \frac{2\pi}{T})x}$$

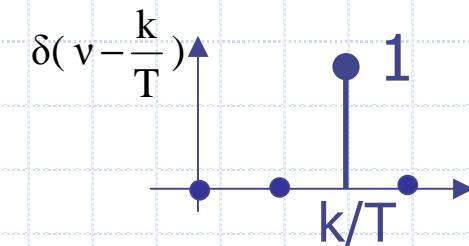
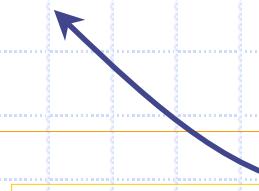
$$\hat{f}(k) = \int_0^T f(x) \cdot e^{-j \cdot (k \frac{2\pi}{T})x} dx$$

Transformée de Fourier

$$f(x) = \int_{-\infty}^{+\infty} \hat{f}(v) \cdot e^{2j\pi vx} dv$$

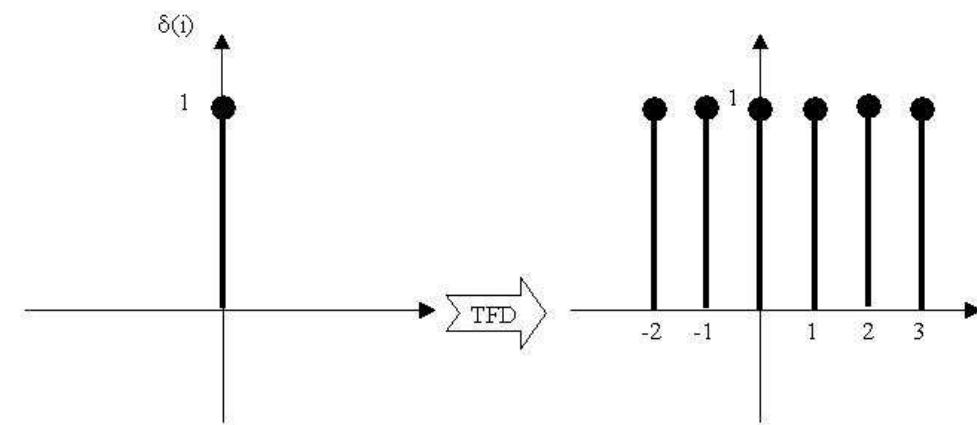
$$\hat{f}(v) = \int_{-\infty}^{+\infty} f(x) \cdot e^{-2j\pi vx} dx$$

$$\hat{f}(v) = \sum_{k \in \mathbb{Z}} \hat{f}(k) \cdot \delta(v - \frac{k}{T})$$



② TFD

TF utiles: impulsion de Dirac

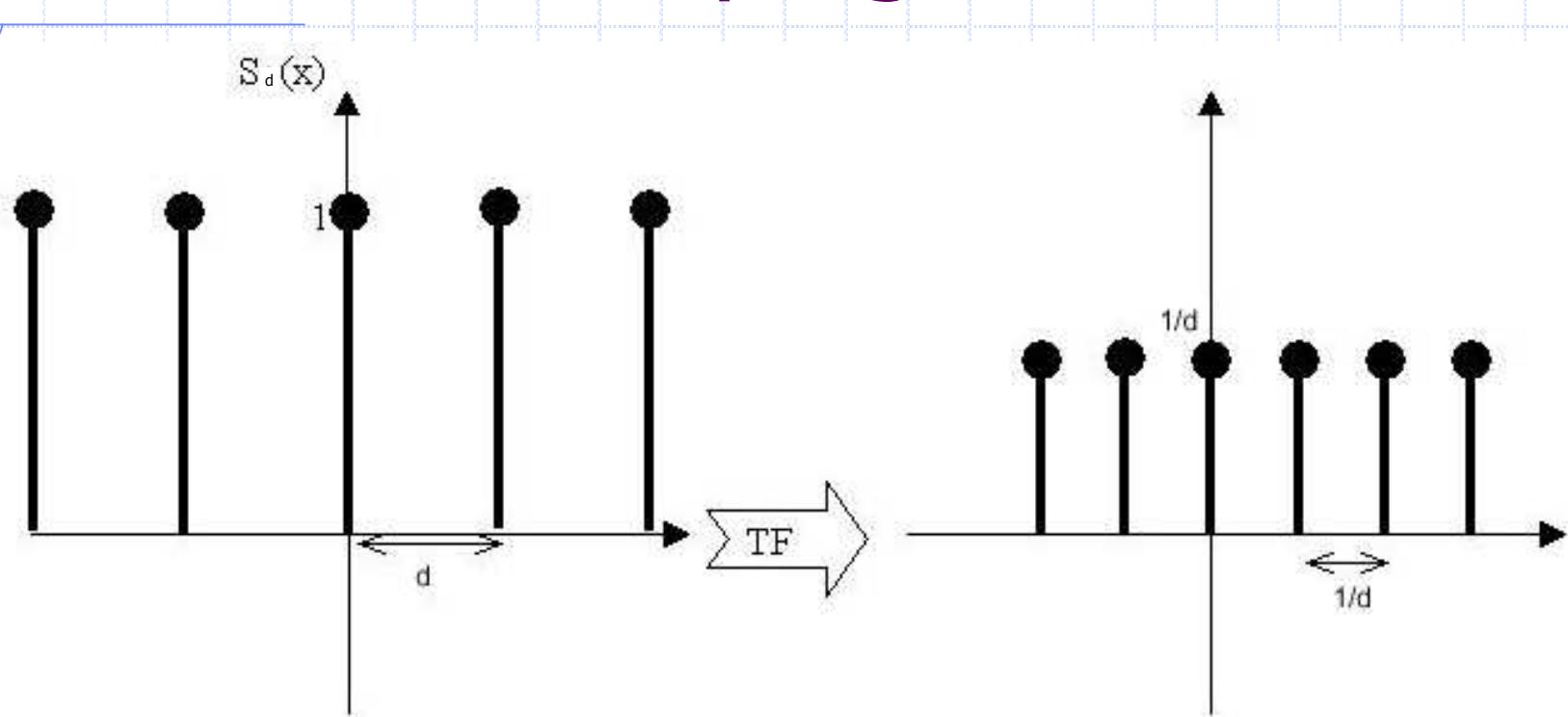


$$\hat{\delta}(v) = \sum_{k=0}^{N-1} \delta(k) e^{-j \cdot (k \frac{2\pi}{N}) v} = \delta(0) e^0 = 1$$

$$\hat{\delta}_R(v) = \sum_{k=0}^{N-1} \delta(k-R) e^{-j \cdot (k \frac{2\pi}{N}) v} = \delta(0) e^{-j \cdot (R \frac{2\pi}{N}) v} = W_N^{R,v}$$

② TFD

TFD utiles : « peigne de Dirac »

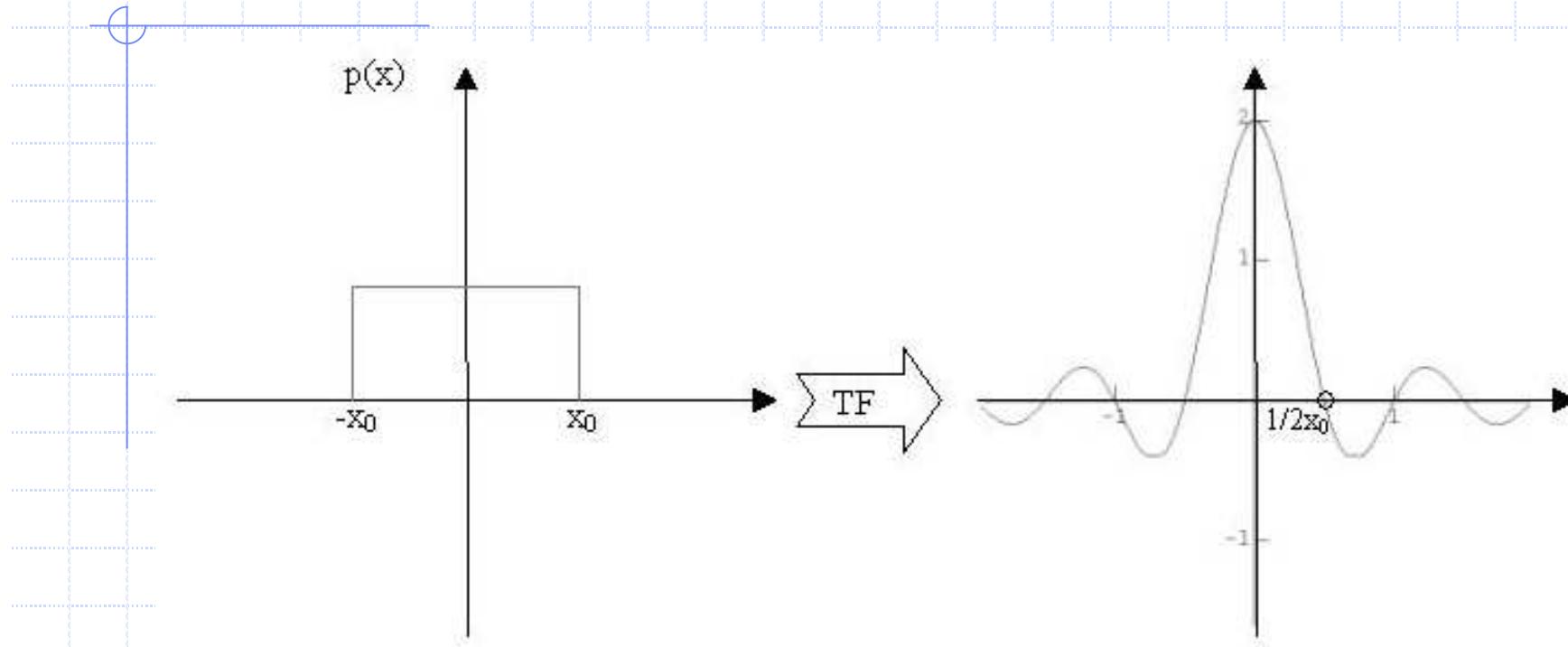


$$S_d(x) = \sum_{k \in \mathbb{Z}} \delta(x - kd)$$

$$\hat{S}(v) = \frac{1}{d} \sum_{k \in \mathbb{Z}} \delta\left(v - \frac{k}{d}\right) = \frac{1}{d} S_1\left(\frac{v}{d}\right)$$

② TFD

TF utiles: créneau

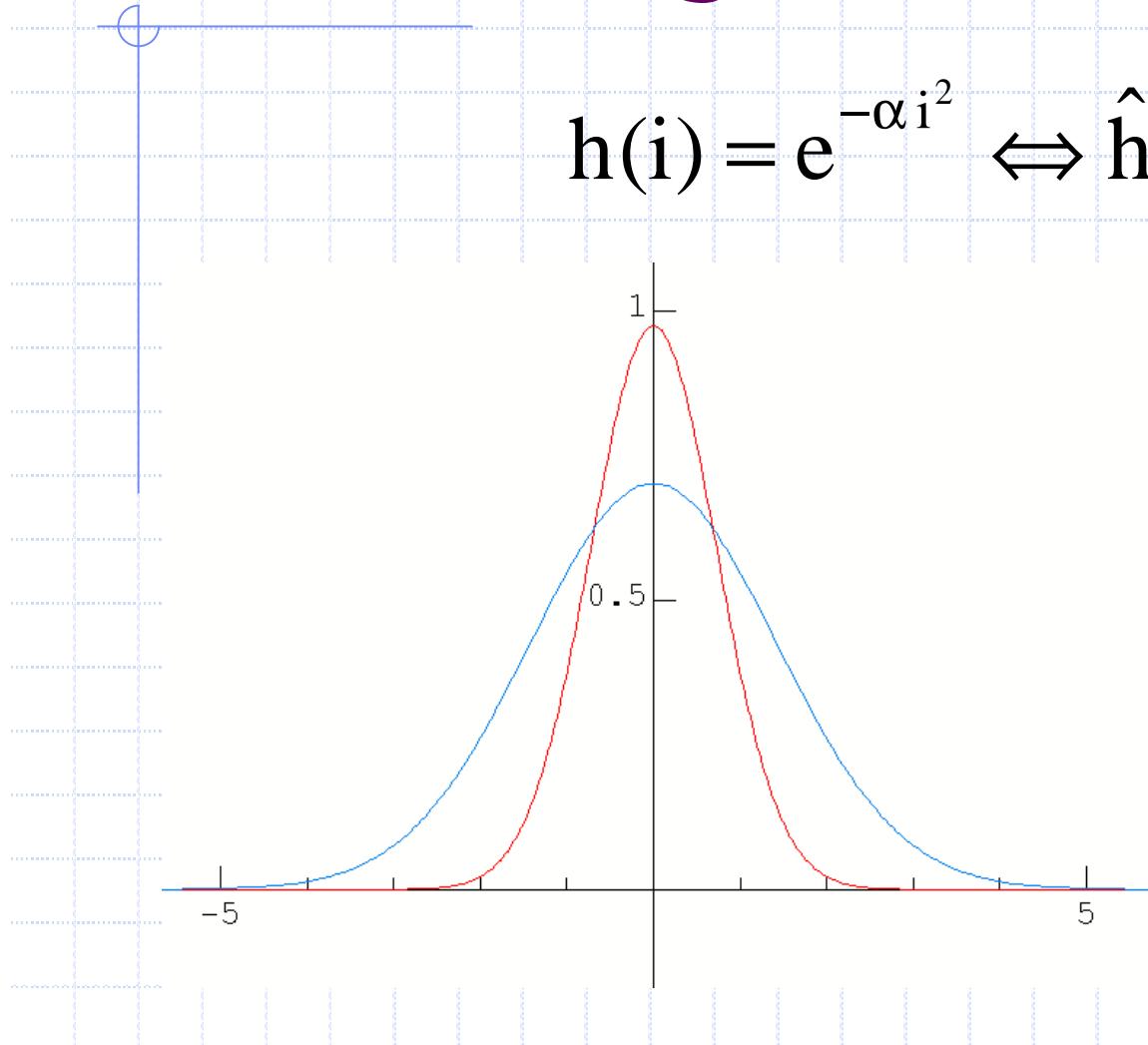


$$\hat{p}(\nu) = \int_{-\infty}^{+\infty} p(x) e^{-2j\pi\nu x} dx = \int_{-x_0}^{+x_0} e^{-2j\pi\nu x} dx = \frac{\sin(2x_0\pi\nu)}{\pi\nu}$$

② TFD

TF utiles: gaussienne

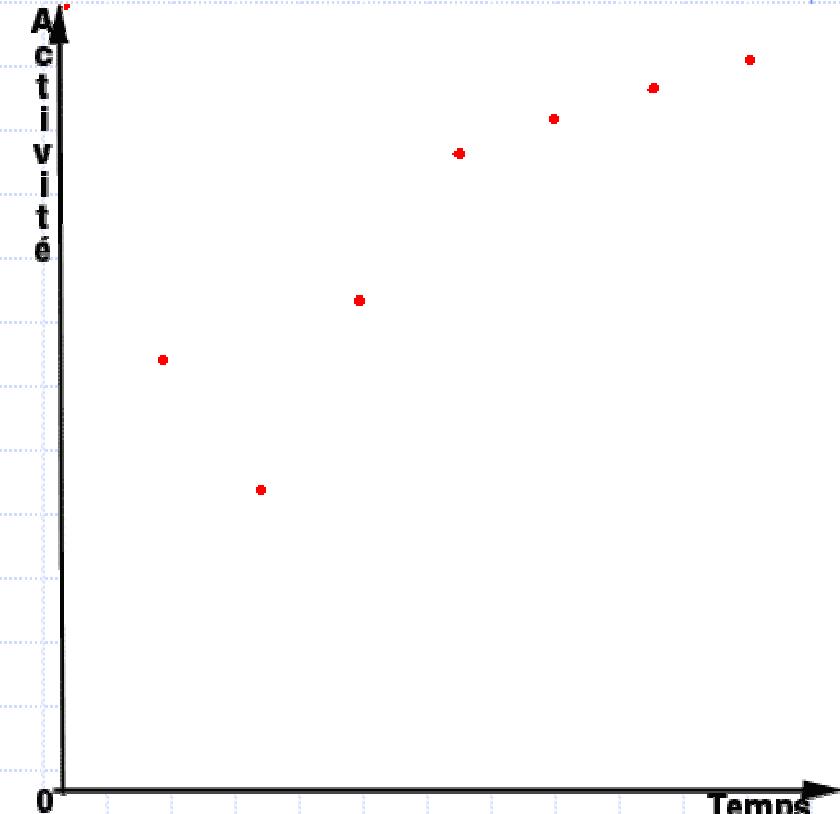
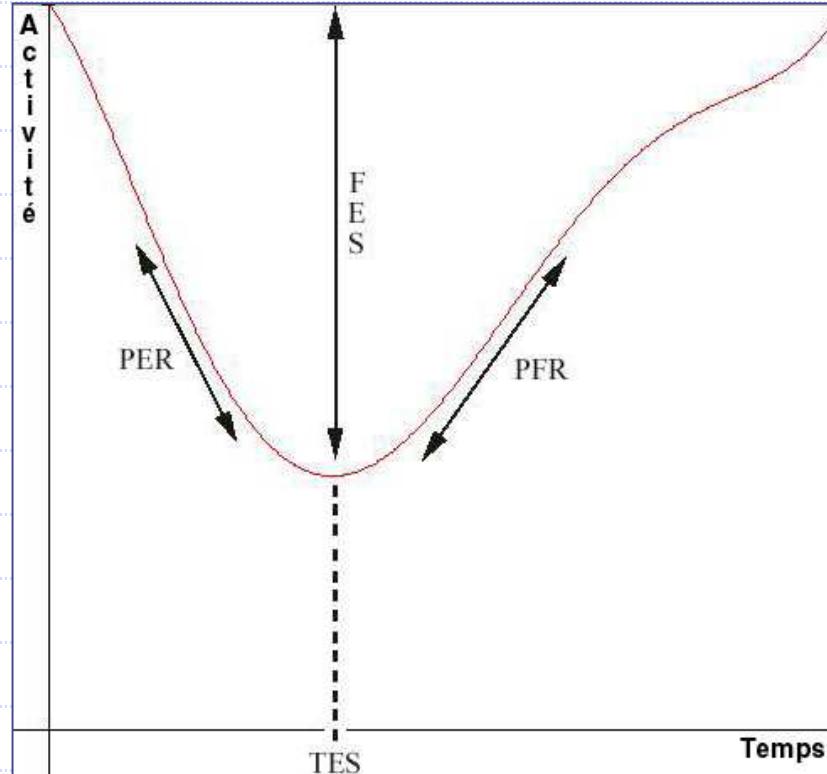
$$h(i) = e^{-\alpha i^2} \Leftrightarrow \hat{h}(v) = \frac{1}{\sqrt{2\alpha}} e^{-\frac{v^2}{4\alpha}}$$



$$Rm : G(i) = \frac{e^{-\frac{i^2}{2\sigma^2}}}{\sigma\sqrt{2\pi}} \Rightarrow \sigma_1 = \frac{1}{\sigma_2}$$

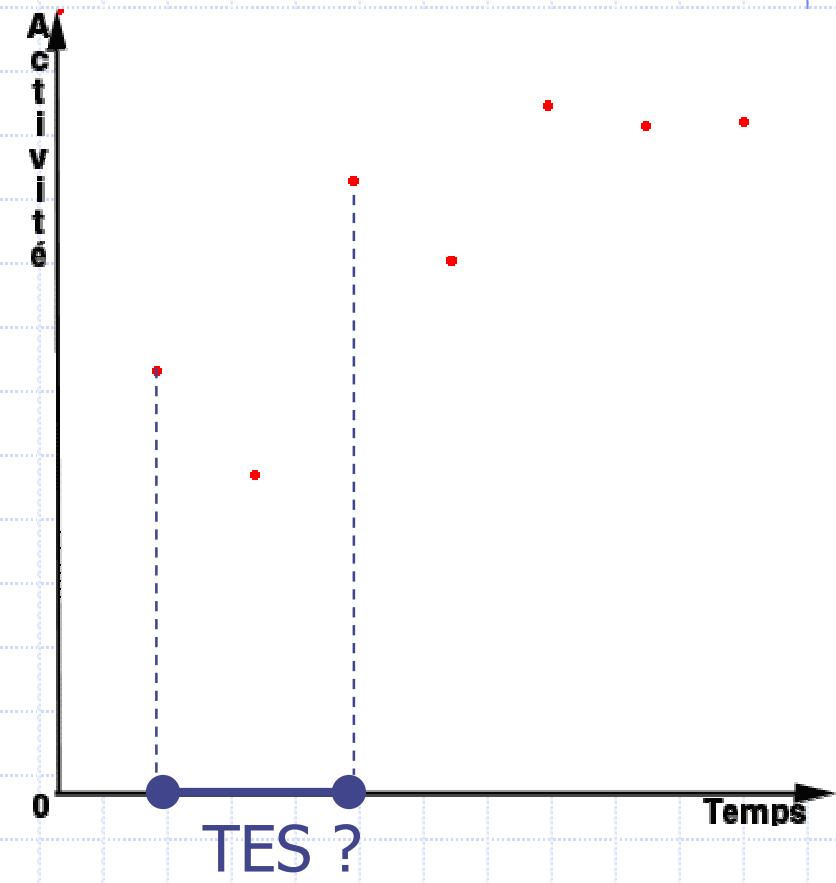
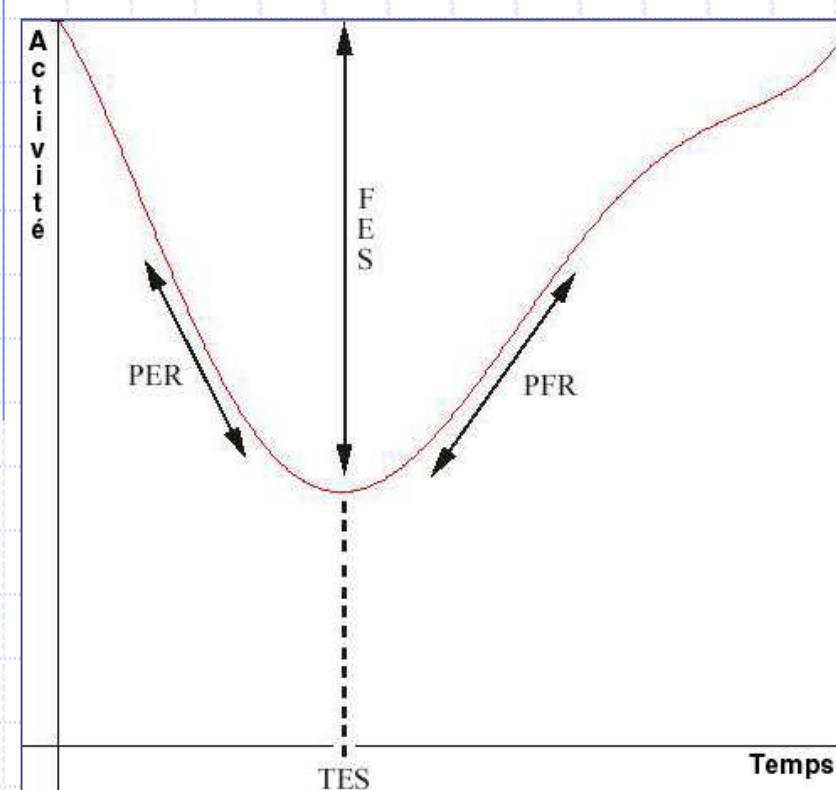
② TFD

Application: détermination des TES



② TFD

Application: détermination des TES

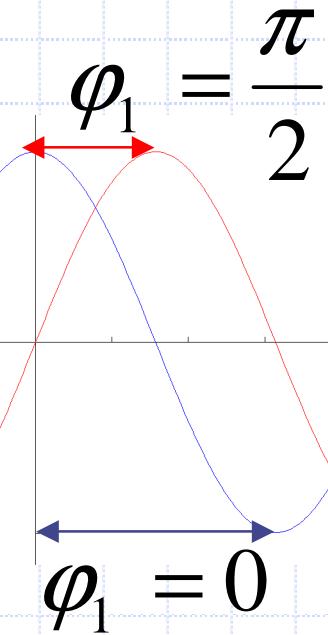
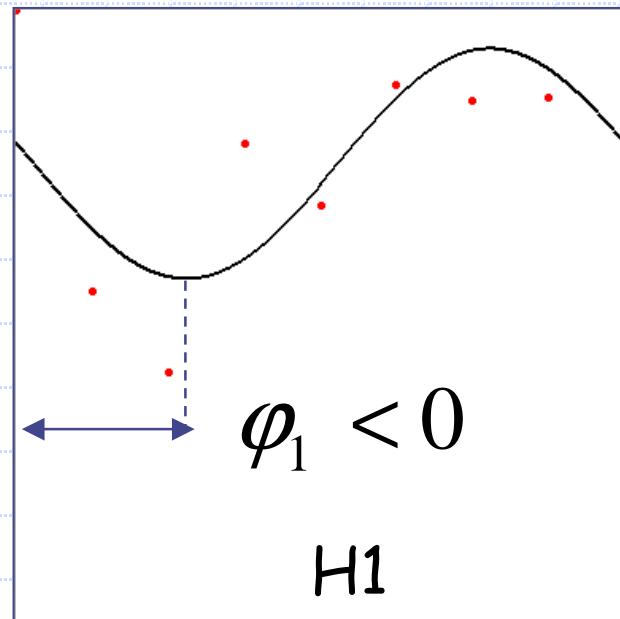


② TFD

1° harmonique

$$s(t) = \frac{1}{N} \sum_{k=0}^{N-1} \hat{s}(k) e^{j(k\omega_0)t}$$

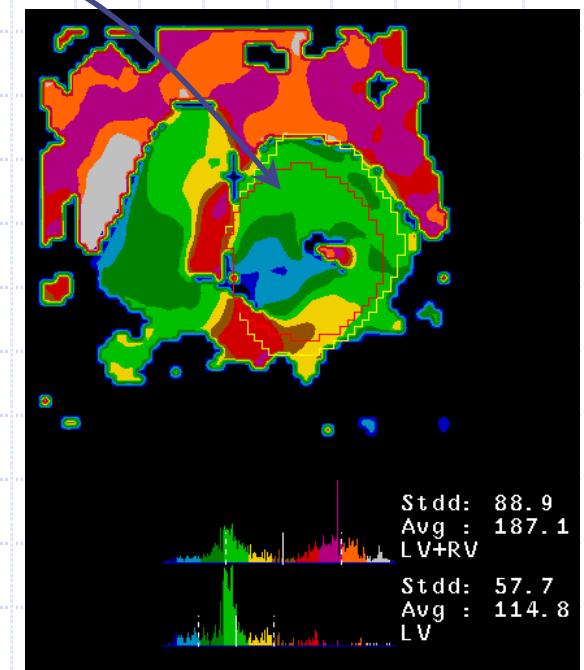
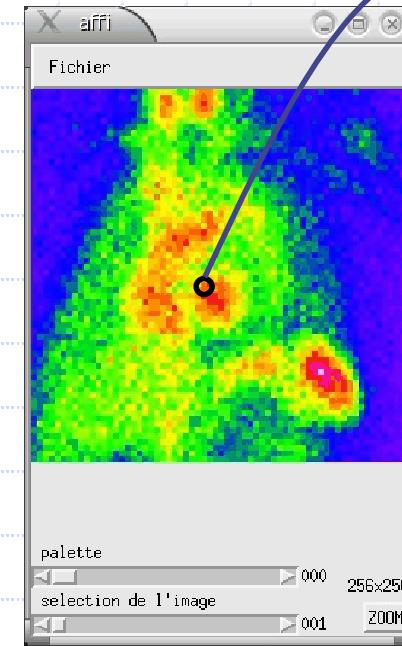
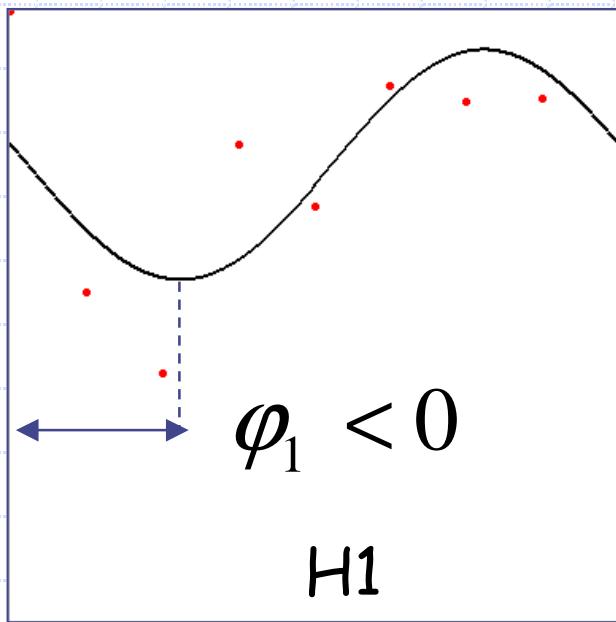
$$s(t) = \frac{\hat{s}(0)}{N} + \frac{\hat{s}(1)}{N} e^{j(\omega_0)t} = A_0 + A_1 e^{j(\omega_0)t + \varphi_1}$$



② TFD

1° harmonique

$$s(t) = A_0 + A_1 e^{j \cdot (\omega_0 t + \varphi_1)}$$

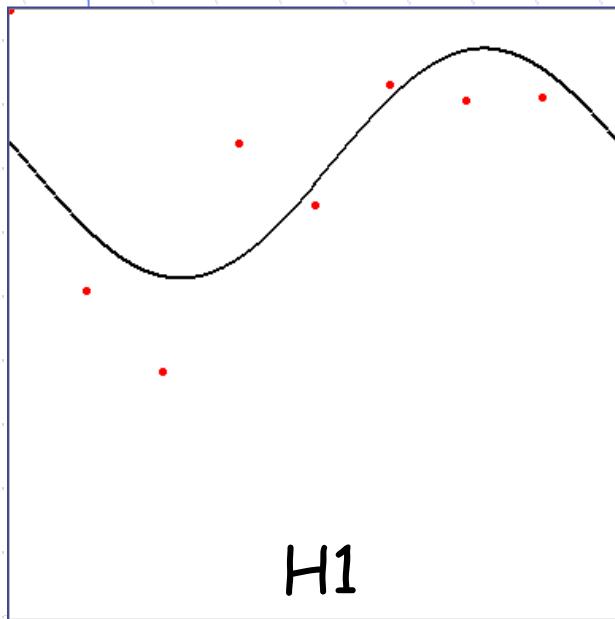


② TFD

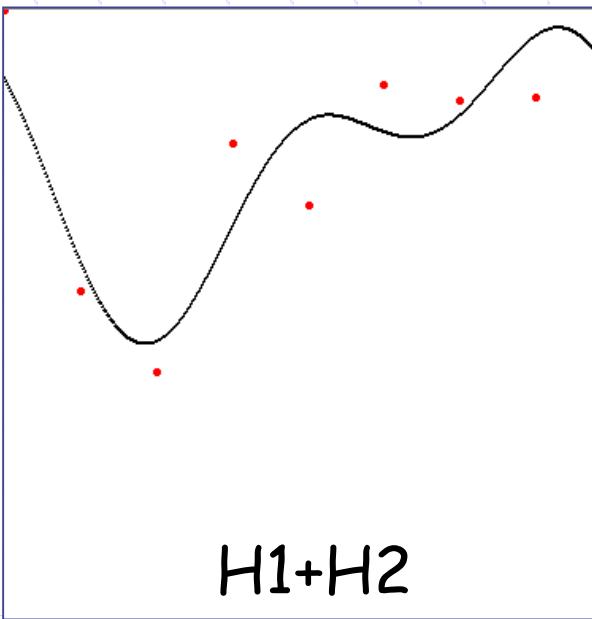
Multi-harmoniques

$$s(t) = \frac{1}{N} \sum_{k=0}^{N-1} \hat{s}(k) \cdot e^{j \cdot (k \omega_0) t}$$

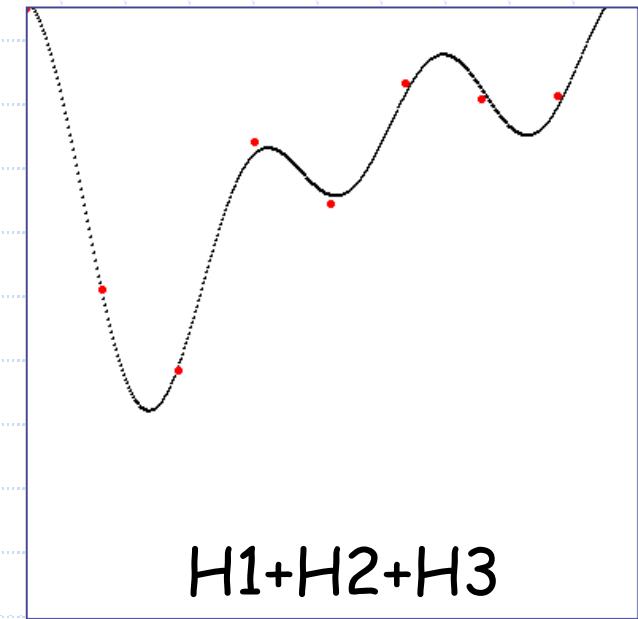
Avant bruitage



H1

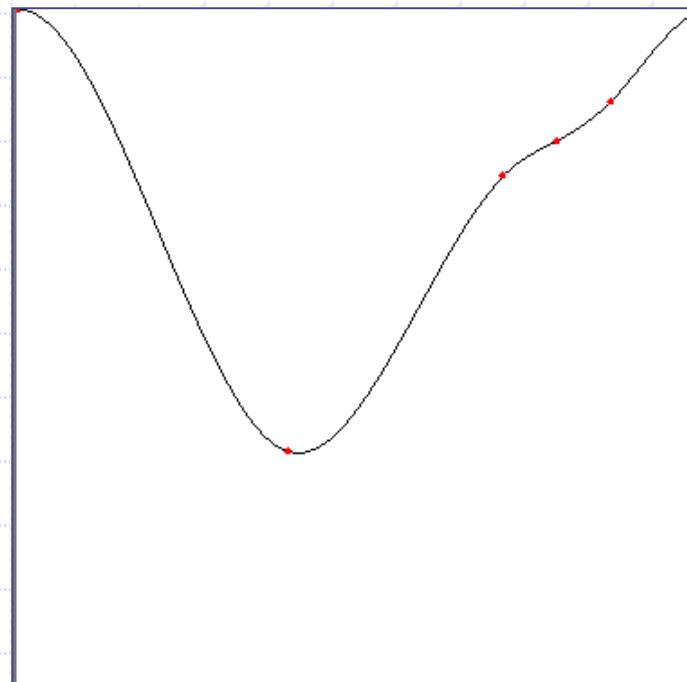


H1+H2

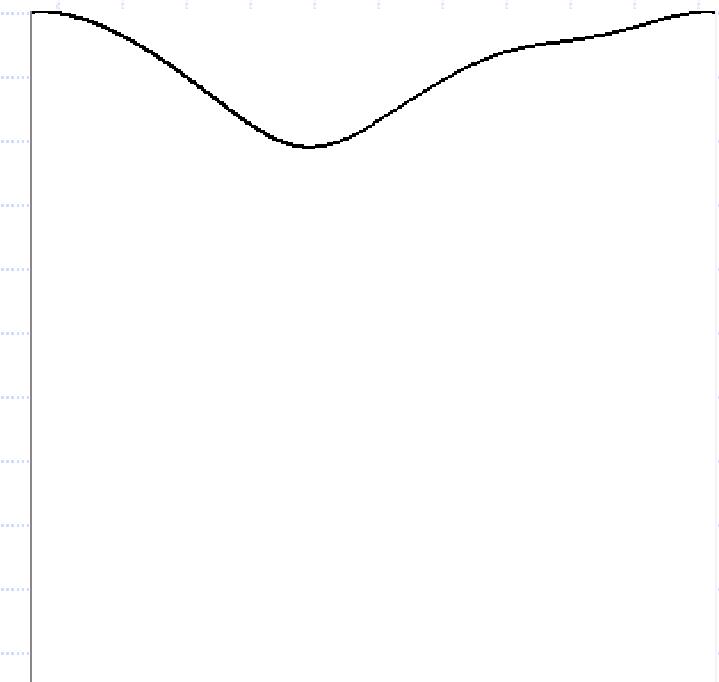
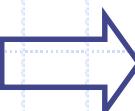


H1+H2+H3

Ajustement en amplitude



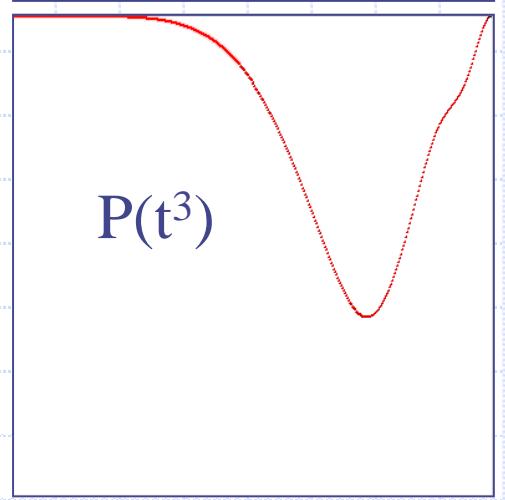
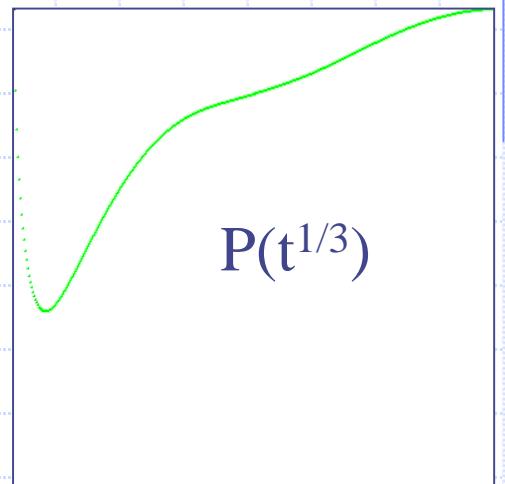
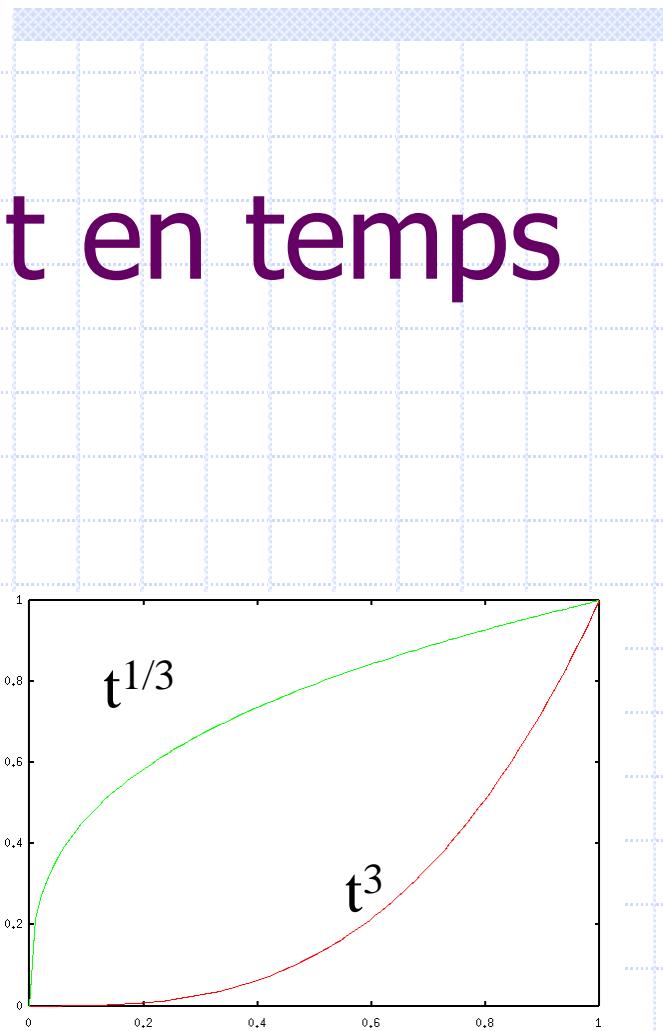
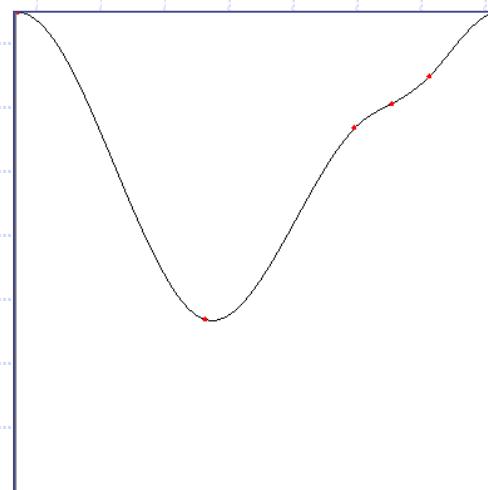
$$P(t)$$



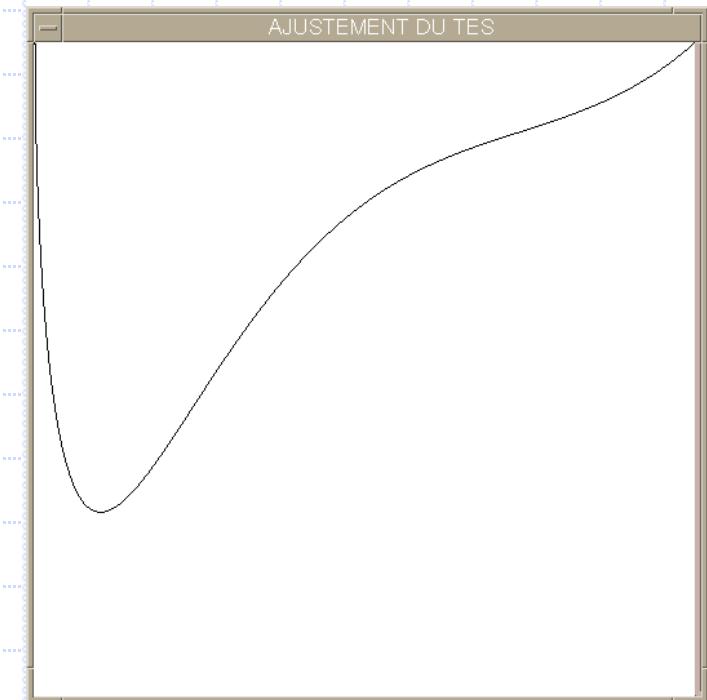
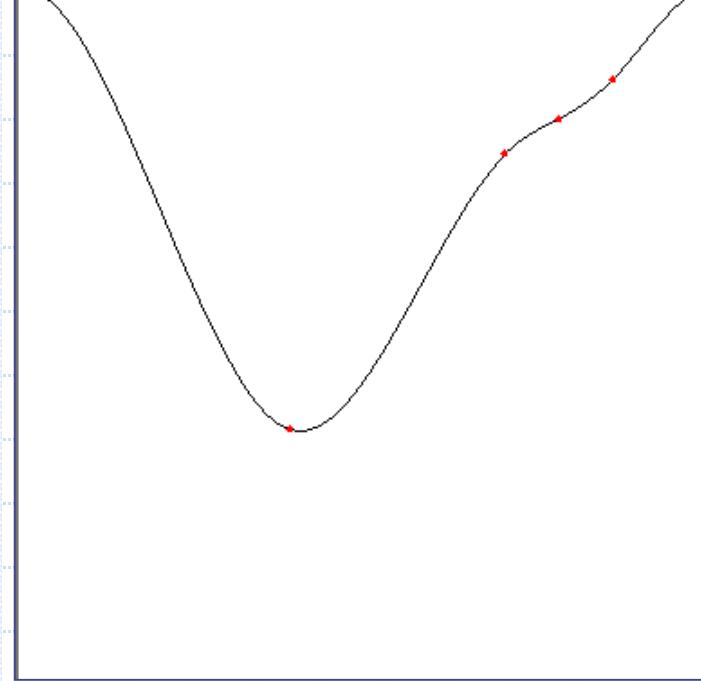
$$D(t) = P(t)^\beta$$

(Caderas de Kerleau et Mariano-Goulart, IEEE TRANS MED IMAGING 2004)

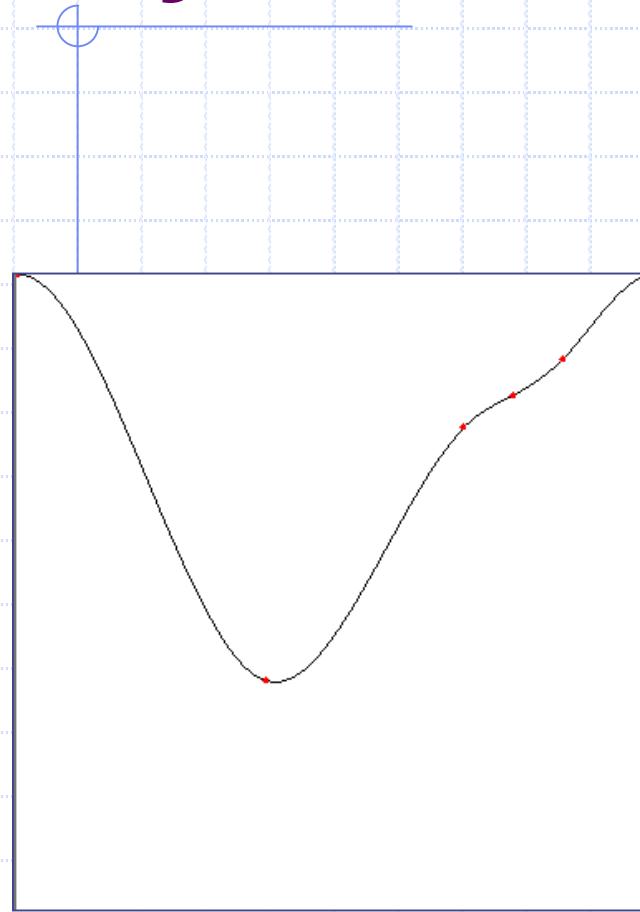
Ajustement en temps



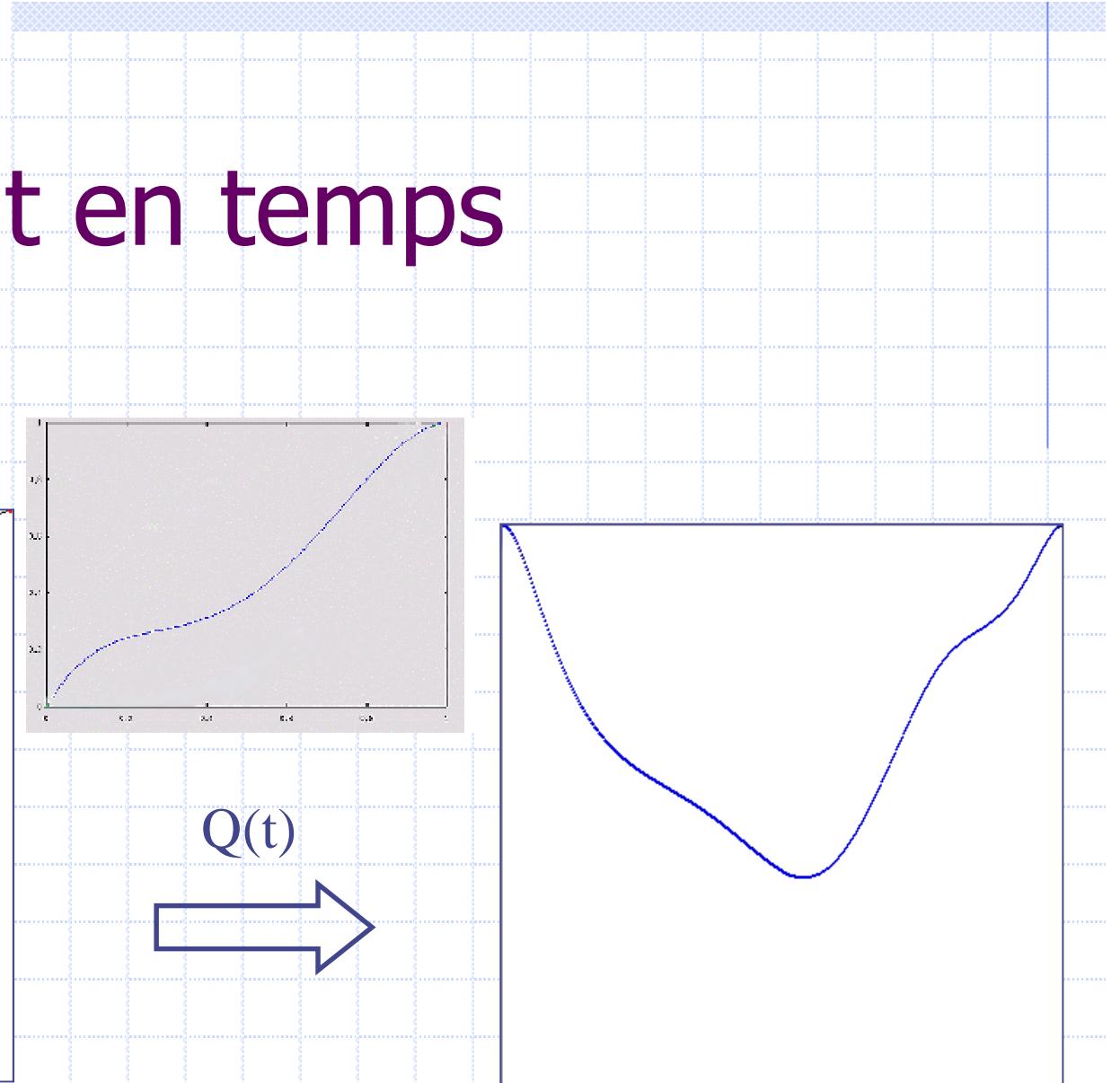
Ajustement en temps



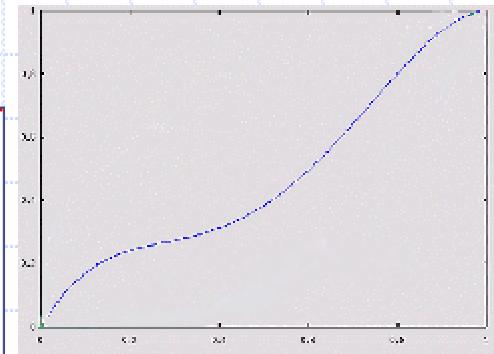
Ajustement en temps



$P(t)$

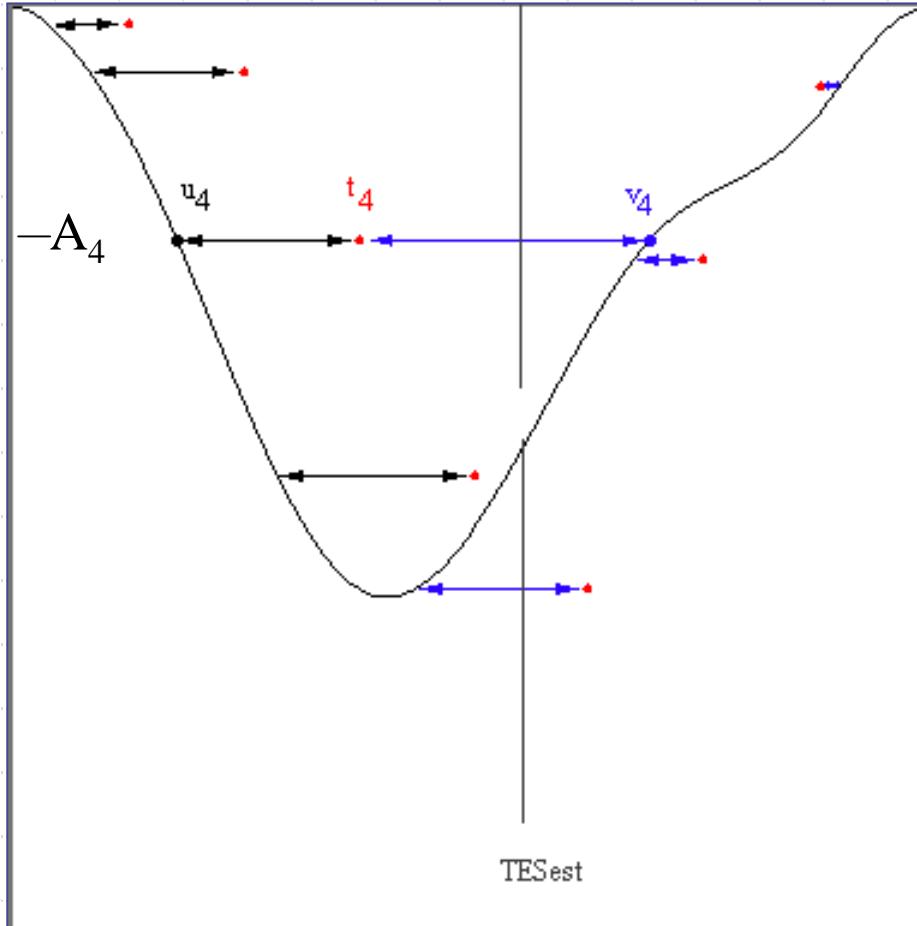


$D(t) = P[Q(t)]$



$Q(t)$

Restauration du signal

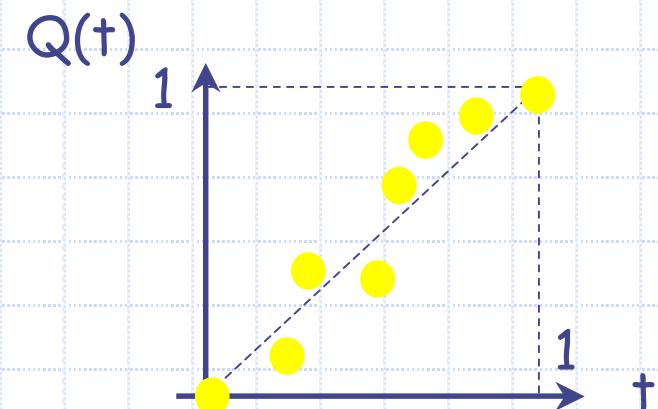


Acquisition bruitée (t_4, A_4)

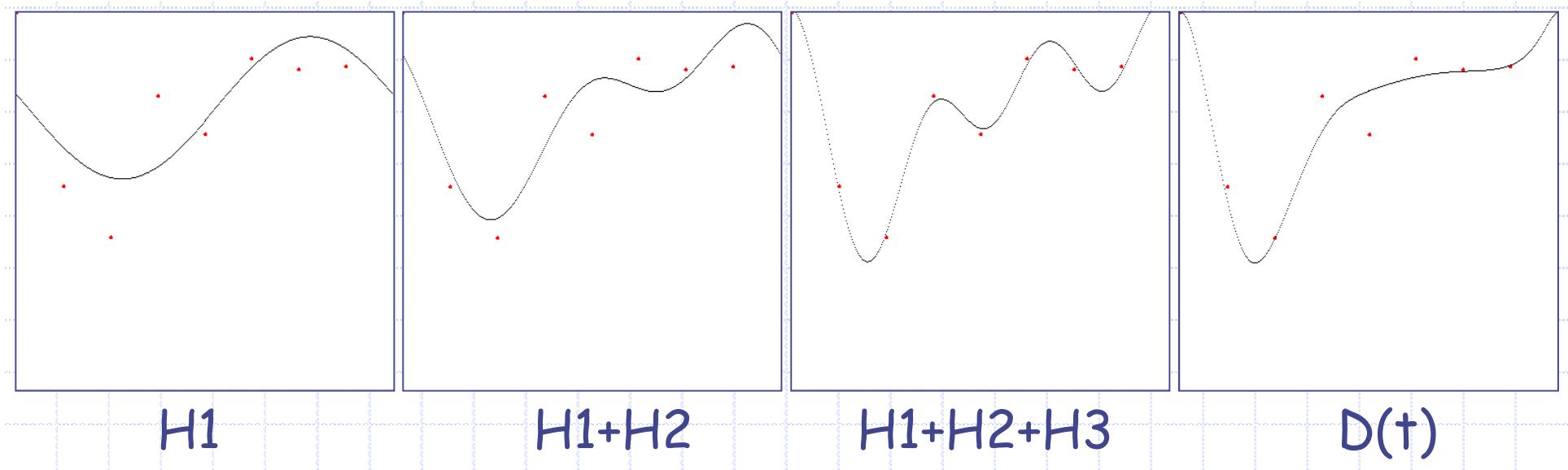
$$A_4 = P(u_4)$$

$$A_4 = D(t_4) = P[Q(t_4)]$$

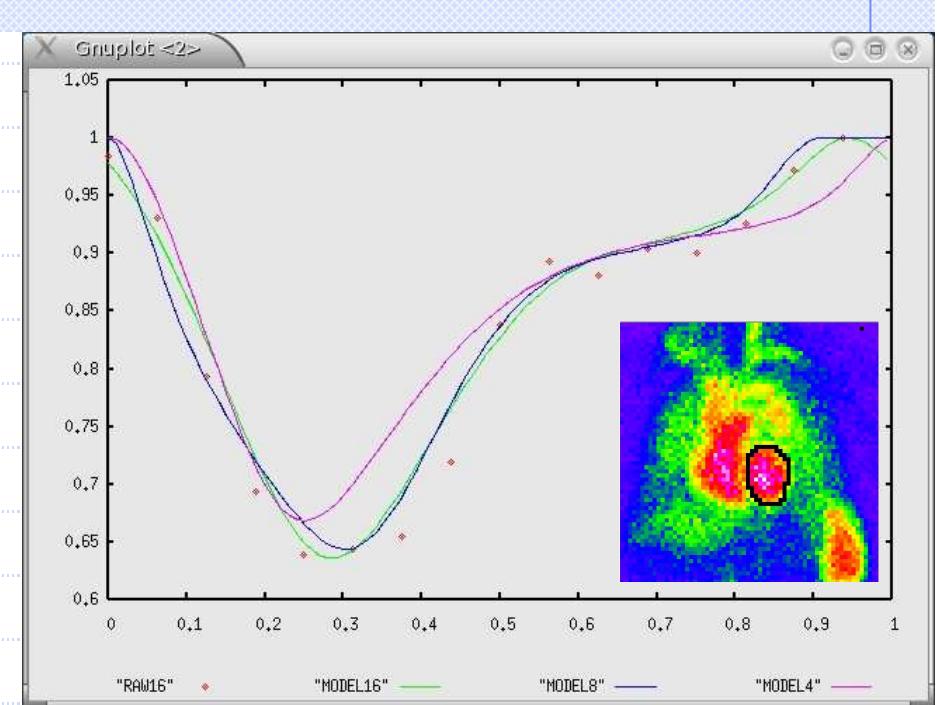
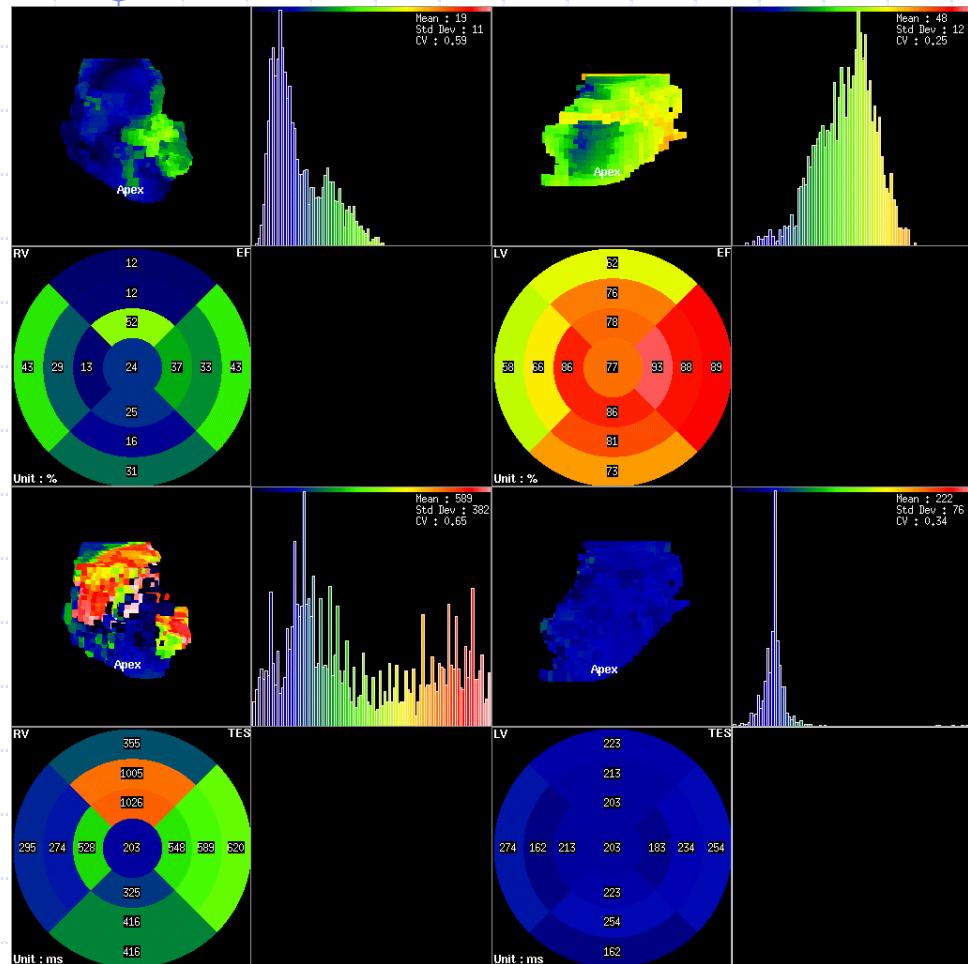
$$Q(t_4) = u_4$$



Résultats (I)



Résultats (II)



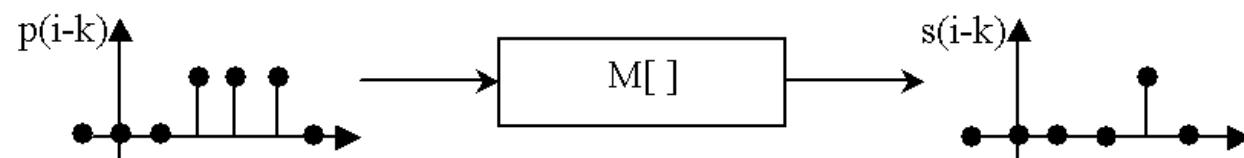
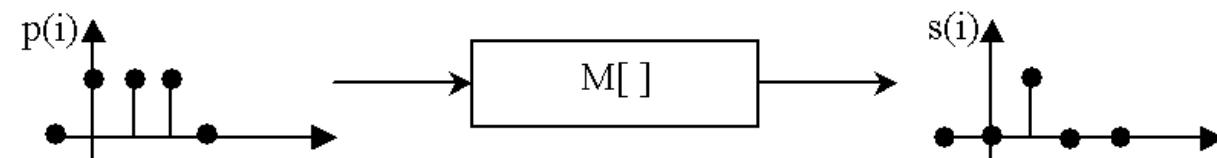
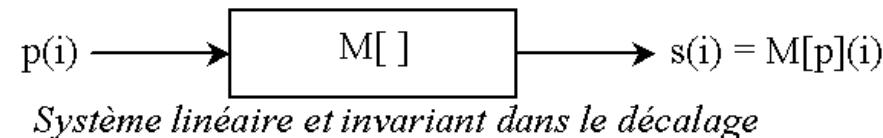
③ Formation de l'image

FORMATION DE L'IMAGE

**SLID
RESOLUTION**

③ Formation de l'image

Systèmes linéaires & invariants dans le décalage

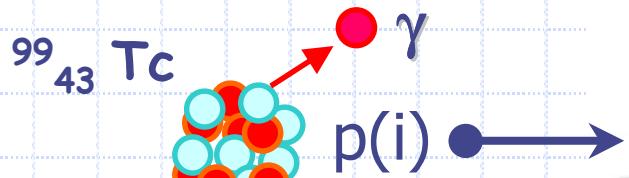


Invariance dans le décalage (dans cet exemple : $k=2$)

③ Formation de l'image

Formation de l'image

$^{99}_{43} \text{Tc}$

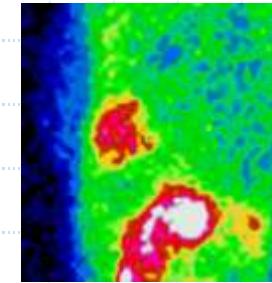


$$p(i) = \sum_{k=-\infty}^{+\infty} p(k) \cdot \delta(i - k)$$

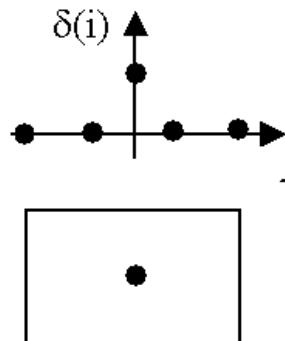


$M[]$

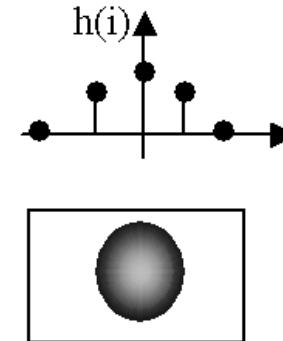
$\bullet \rightarrow s(i)$



$$s(i) = \sum_{k=-\infty}^{+\infty} p(k) \cdot M[\delta](i - k)$$



$M[]$



$$s(i) = \sum_{k=-\infty}^{+\infty} p(k) \cdot h(i - k)$$

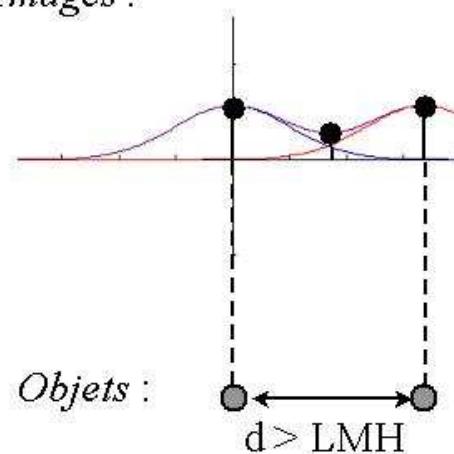
$$s = p * h = h * p$$

Produit de convolution
 $R_m : p = \delta * p$

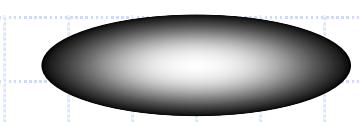
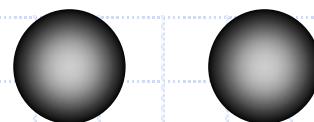
③ Formation de l'image

Interprétation (I)

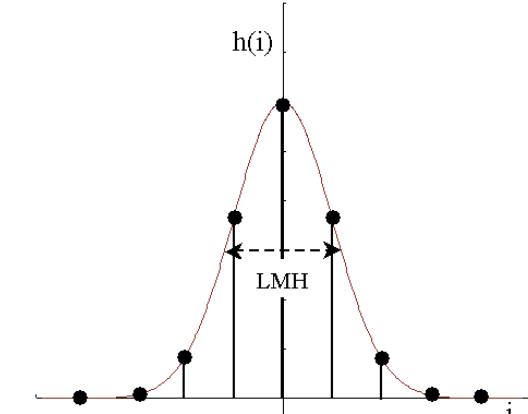
Images :



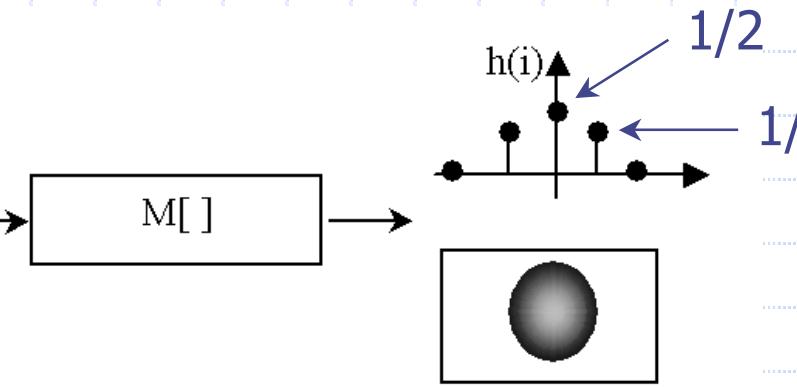
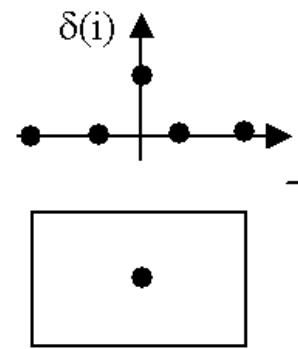
Objets :



LMH = pouvoir séparateur = résolution de l'image
1/LMH = fréquence spatiale maximale dans le signal



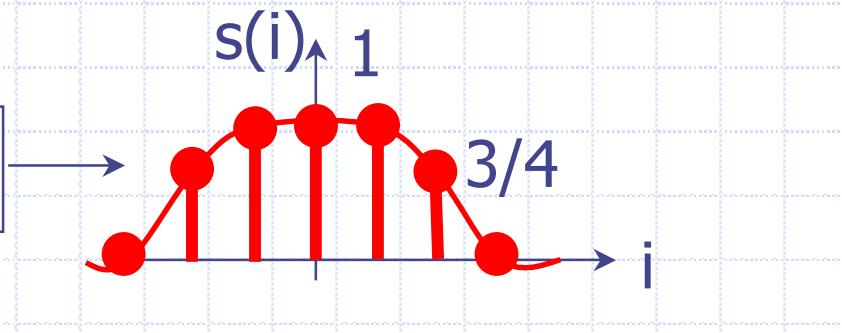
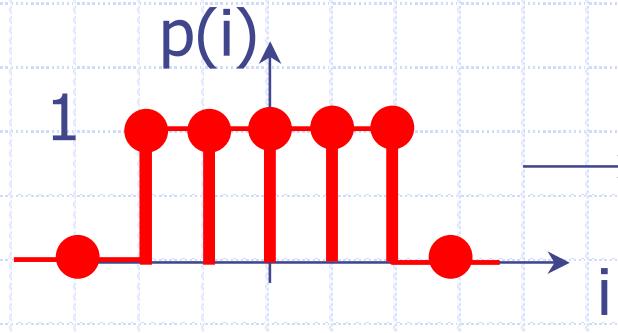
Interprétation (II)



$$s(i) = \sum_{k=-1}^{+1} h(k) \cdot p(i-k)$$

$$s(i) = \frac{1}{4}p(i+1) + \frac{1}{2}p(i) + \frac{1}{4}p(i-1) = \frac{2.p(i)+p(i+1)+p(i-1)}{4}$$

moyenne pondérée



③ Formation de l'image

SLID et base de Fourier

$$p(i) = e^{j \cdot (v \omega_0) i} \rightarrow M[\] \rightarrow s(i) = M[p](i)$$

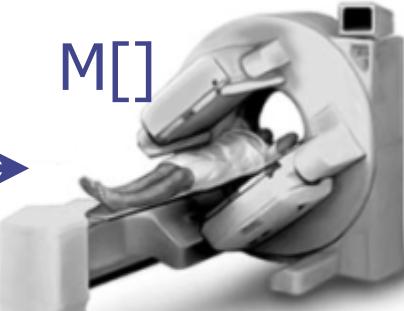
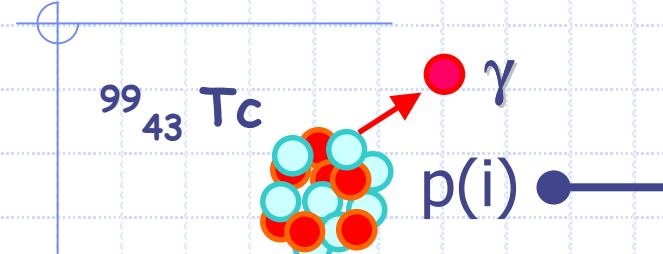
$$s(i) = \sum_{k=-\infty}^{k=+\infty} h(k) \cdot e^{j \cdot (v \cdot \omega_0) \cdot (i-k)} = e^{j \cdot (v \cdot \omega_0) \cdot i} \sum_{k=-\infty}^{k=+\infty} h(k) \cdot e^{-j \cdot (v \cdot \omega_0) \cdot k}$$

$$p(i) = e^{j \cdot (v \omega_0) i} \Rightarrow M[p](i) = \hat{h}(v) \cdot p(i)$$

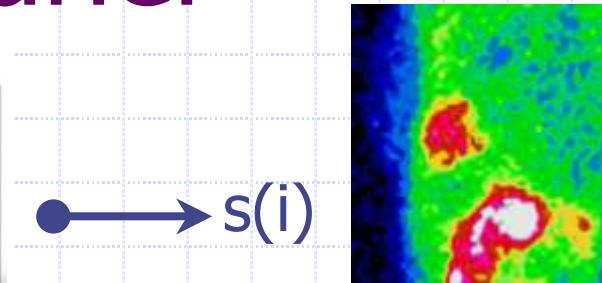
Un SLID agit sur l'harmonique v
en l'amplifiant par la réponse en fréquence en v

③ Formation de l'image

SLID et base de Fourier



ACQUISITION



$$p(i) = \frac{1}{N} \sum_{v=0}^{v=N-1} \hat{p}(v) e^{j\omega_0 \cdot v \cdot i}$$

$$\Rightarrow M[p](i) = \frac{1}{N} \sum_{v=0}^{v=N-1} \hat{p}(v) \hat{h}(v) e^{j\omega_0 \cdot v \cdot i}$$

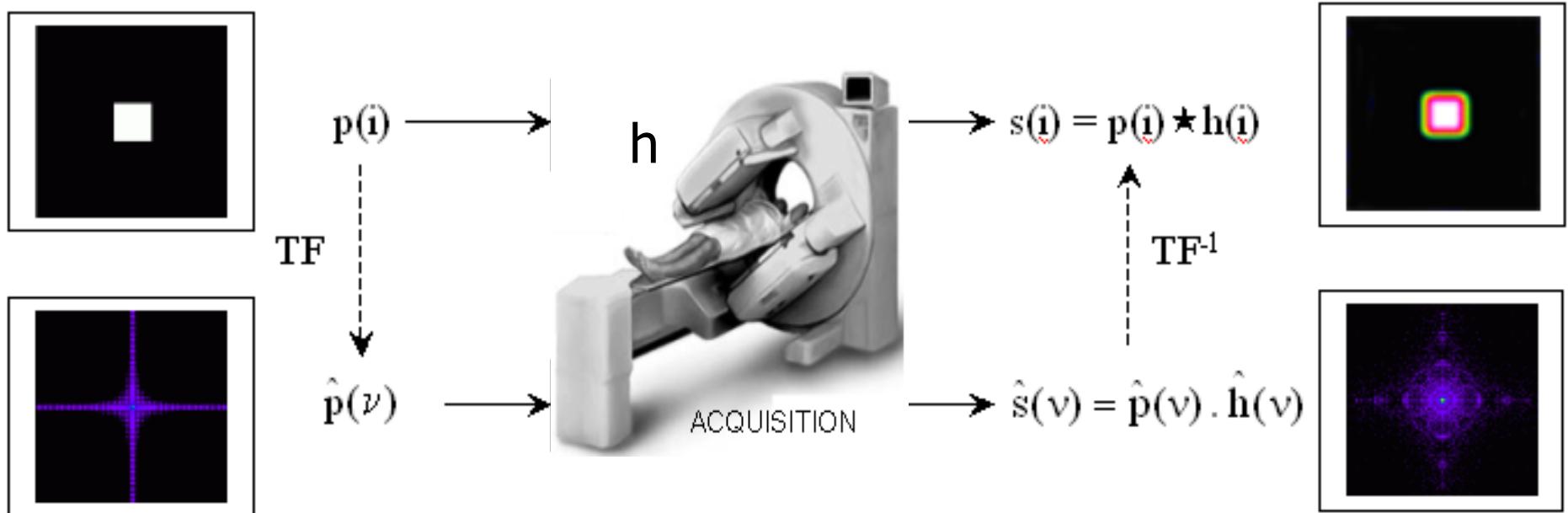
$$s(i) = \frac{1}{N} \sum_{v=0}^{v=N-1} \hat{s}(v) e^{j\omega_0 \cdot v \cdot i}$$

$s = p * h \Rightarrow \hat{s} = \hat{p} \cdot \hat{h}$

Rm: $s = \delta * h = h \Rightarrow \hat{s} = \hat{\delta} \cdot \hat{h} = \hat{h}$, d'où $\hat{\delta} = 1$

③ Formation de l'image

Formation de l'image: synthèse



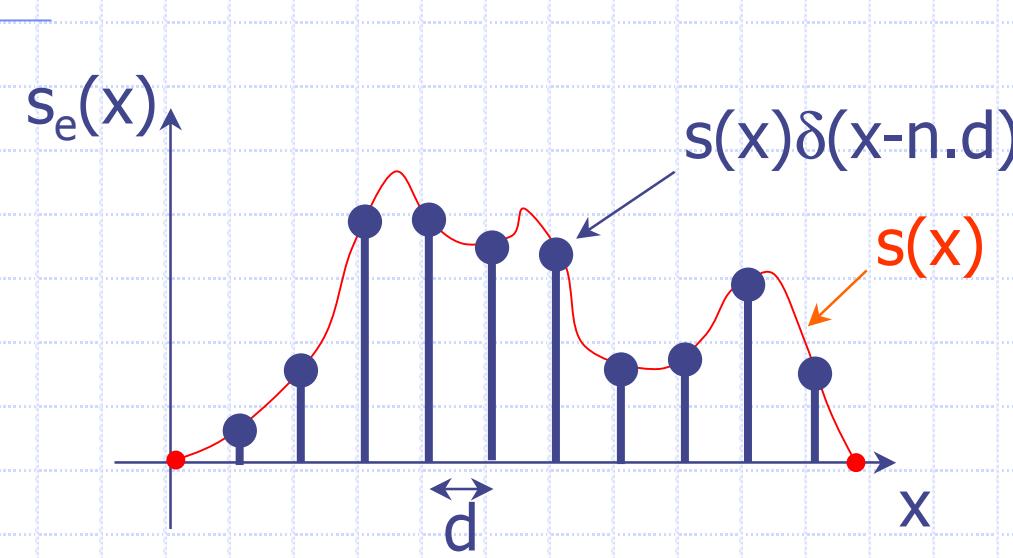
④ Théorème de Shannon

ECHANTILLONNAGE

THEOREME DE SHANNON

④ Théorème de Shannon

Opérateur d'échantillonnage



$$s_e(x) = s(x) \cdot S_d(x) = \sum_{n=-\infty}^{+\infty} s(n.d) \cdot \delta(x - n.d)$$

④ Théorème de Shannon

Théorème de Shannon (I)

$$s_e(x) = s(x) \cdot \sum_{n=-\infty}^{+\infty} \delta(x - nd)$$

$$\hat{s}_e(v) = \frac{1}{d} \hat{s}(v) * \sum_{n=-\infty}^{+\infty} \delta\left(v - \frac{n}{d}\right)$$

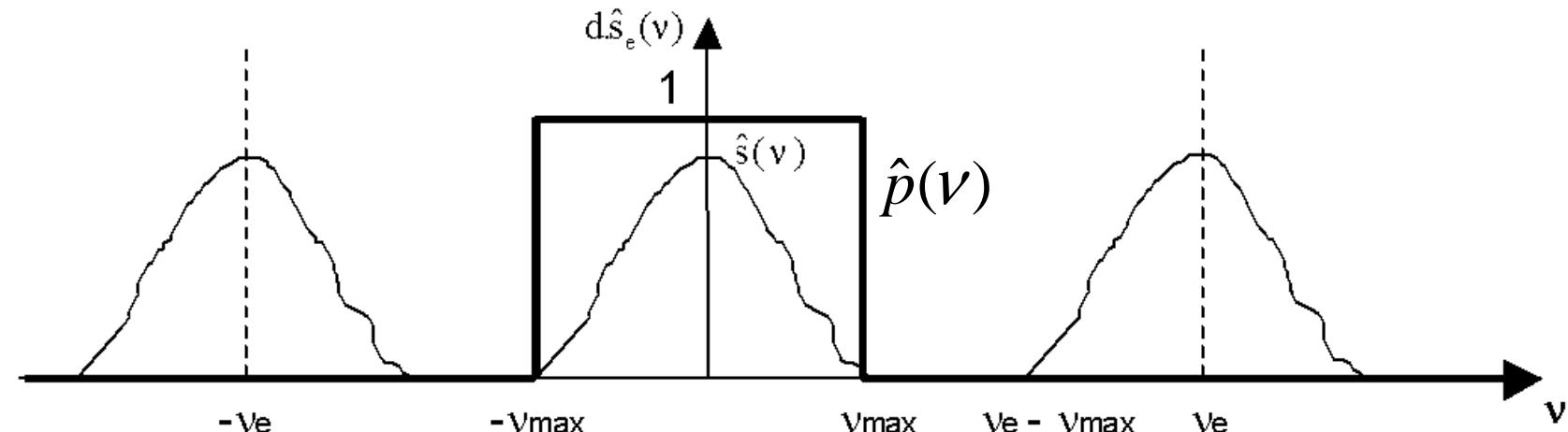
mais $\hat{s}(v) * \delta\left(v - \frac{n}{d}\right) = \sum_{k=-\infty}^{+\infty} \hat{s}(k) \cdot \delta\left(v - \frac{n}{d} - k\right) = \hat{s}\left(v - \frac{n}{d}\right)$

donc $\hat{s}_e(v) = \frac{1}{d} \sum_{n=-\infty}^{+\infty} \hat{s}\left(v - \frac{n}{d}\right)$

④ Théorème de Shannon

Théorème de Shannon (II)

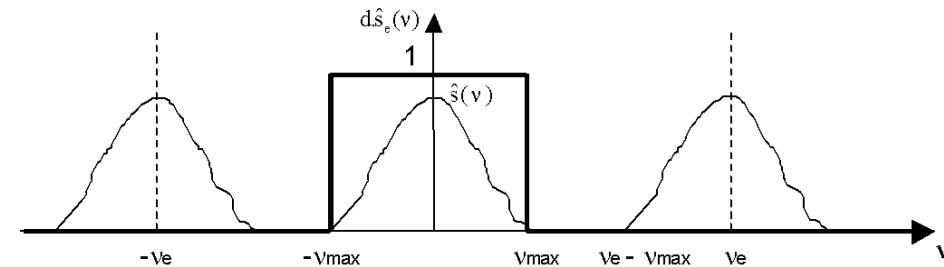
$$d \cdot \hat{s}_e(v) = \sum_{n=-\infty}^{+\infty} \hat{s}\left(v - \frac{n}{d}\right)$$



$$V_e > 2 \cdot V_{\max} \Rightarrow d \cdot \hat{s}_e(v) \cdot \hat{p}(v) = \hat{s}(v)$$

④ Théorème de Shannon

Théorème de Shannon (III)



$$V_e > 2.V_{\max} \Rightarrow d.\hat{s}_e(v).\hat{p}(v) = \hat{s}(v)$$

$$s(x) = d.p(x) * \sum_{n=-\infty}^{\infty} s(n.d) \cdot \delta(x - n.d) = d \cdot \sum_{n=-\infty}^{\infty} s(n.d) p(x - n.d)$$

$$s(x) = d \cdot \sum_{n=-\infty}^{\infty} s(n.d) \cdot \frac{\sin[2\pi V_{\max} (x - n.d)]}{\pi(x - n.d)}$$

④ Théorème de Shannon

Théorème de Shannon (IV)

$$\nu_e > 2\nu_{\max} \Rightarrow s(x) = d \cdot \sum_{n=-\infty}^{\infty} s(n.d) \cdot \frac{\sin[2\pi\nu_{\max}(x-n.d)]}{\pi(x-n.d)}$$

donc échantillonnage sans perte d'information

$2\nu_{\max}$ = 2/LMH est appelé fréquence de Nyquist

*Exemple : Nombre de pixels en scintigraphie myocardique
champ 50x50 cm
LMH = 16 mm*

④ Théorème de Shannon

Théorème de Shannon (IV)

$$v_e > 2.v_{\max} \Rightarrow s(x) = d \cdot \sum_{n=-\infty}^{\infty} s(n.d) \cdot \frac{\sin[2\pi v_{\max}(x-n.d)]}{\pi(x-n.d)}$$

donc échantillonnage sans perte d'information

$2.v_{\max}$ = 2/LMH est appelé fréquence de Nyquist

*Exemple : Nombre de pixels en scintigraphie myocardique
champ 50x50 cm*

$LMH = 16 \text{ mm}$

Réponse:

$$v_{\max} = 1/LMH = 1/16 = 0.0625 \text{ pixel/mm}$$

$$v_e = 2.v_{\max} = 2/16 = 0.125 \text{ pixel/mm}$$

Donc $0.125 \times 500 = 62.5$ i.e 64 pixels/côté

⑤ Filtrage linéaire

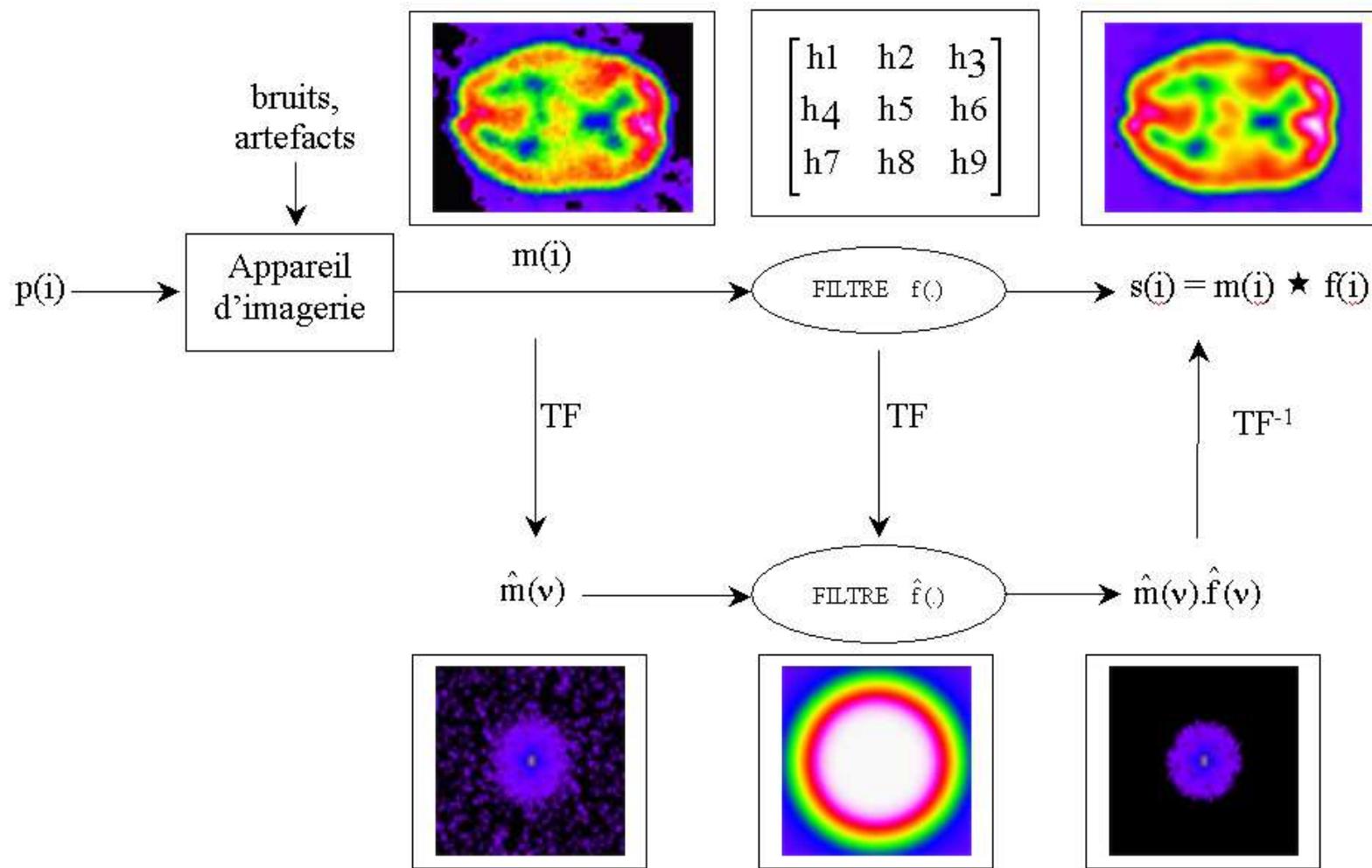
FILTRAGE

Filtrage linéaire (et invariant dans le décalage)

Filtrage non linéaire

⑤ Filtrage linéaire

Filtrage linéaire d'image



Filtres passe-bas

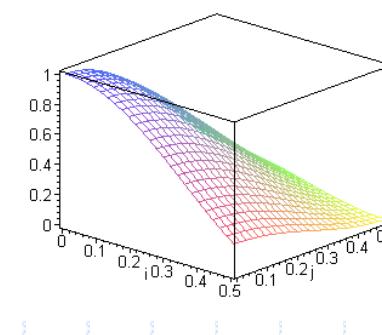
◆ Convolution: $s(i) = \sum_{k=-\infty}^{+\infty} f(k) \cdot m(i-k)$

◆ Remplace chaque NG par une moyenne pondérée des NG voisins

$$\frac{1}{16} \begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$$

◆ Atténuation sélective de certaines fréquences

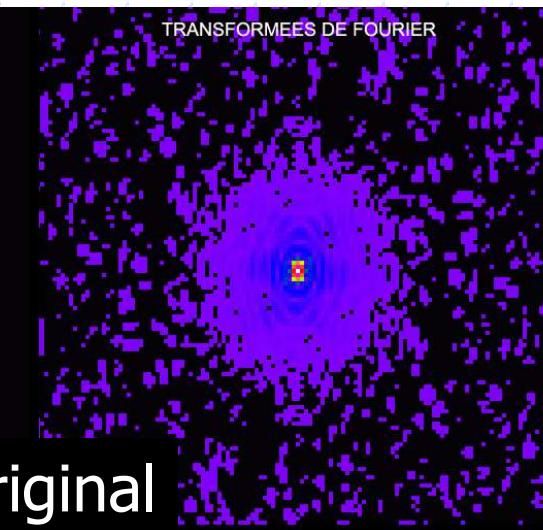
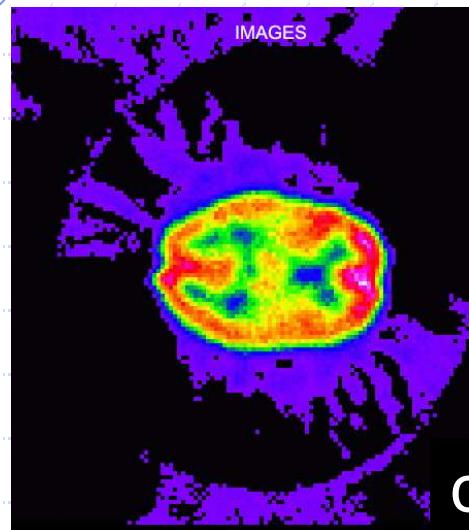
$$\hat{f}(\nu) = 0,5 \cdot [1 + \cos(\pi \frac{\nu}{\nu_e})]$$



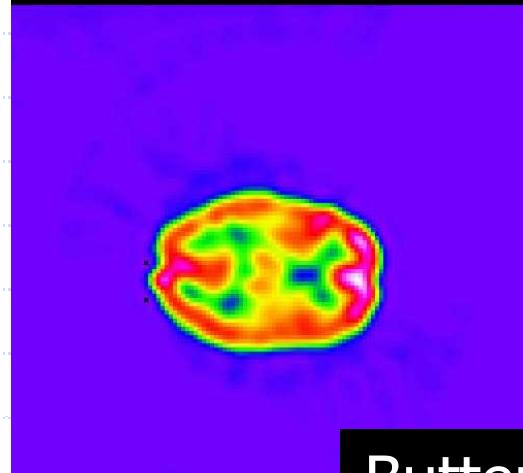
$$\sqrt{\nu^2 + \nu'^2}$$

⑤ Filtrage linéaire

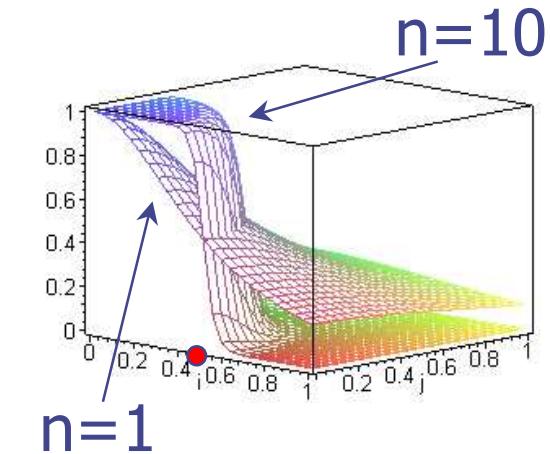
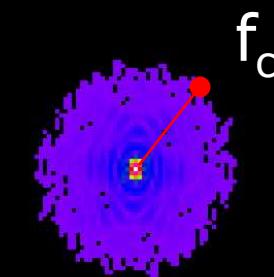
Exemple: filtres de Butterworth



original

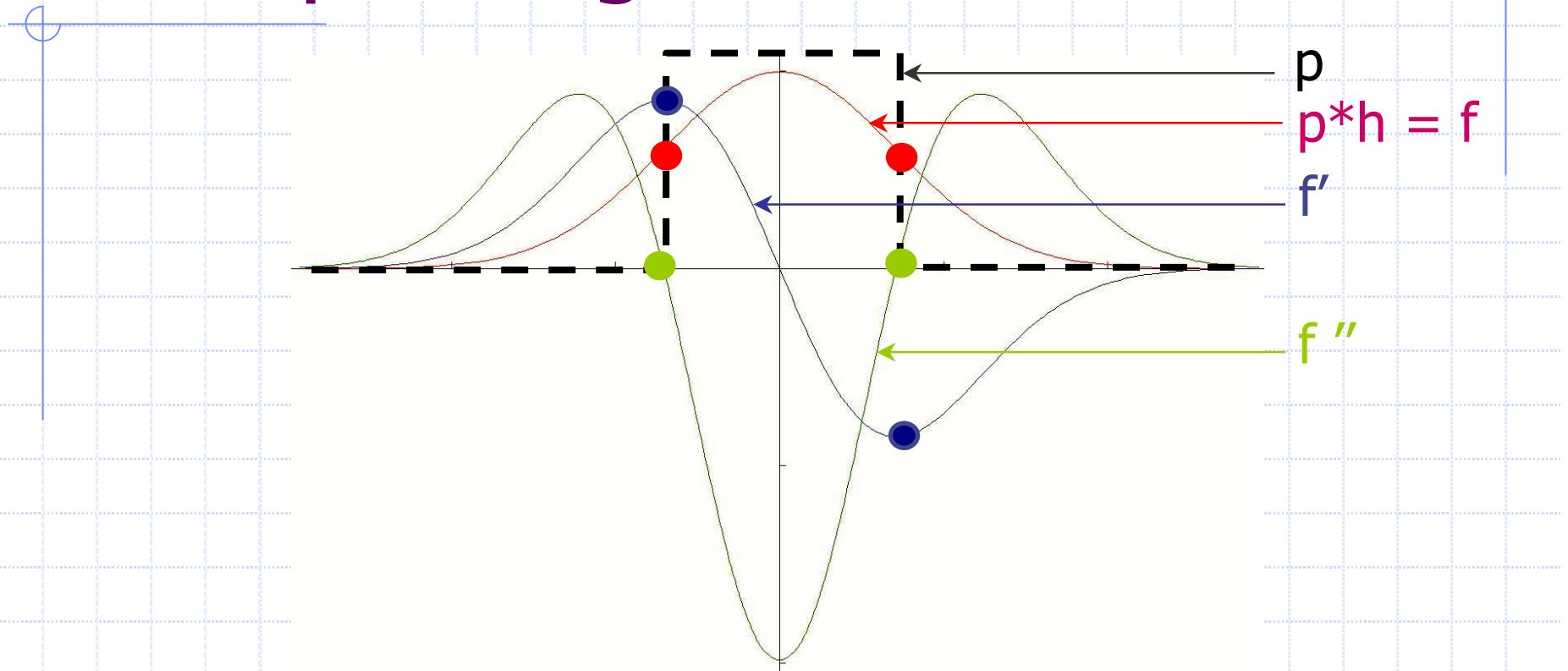


Butterworth



$$\hat{m}(\nu, \nu') = \frac{1}{1 + \left(\frac{\sqrt{\nu^2 + \nu'^2}}{f_c} \right)^{2n}}$$

Exemple: segmentation



◆ Frontières :

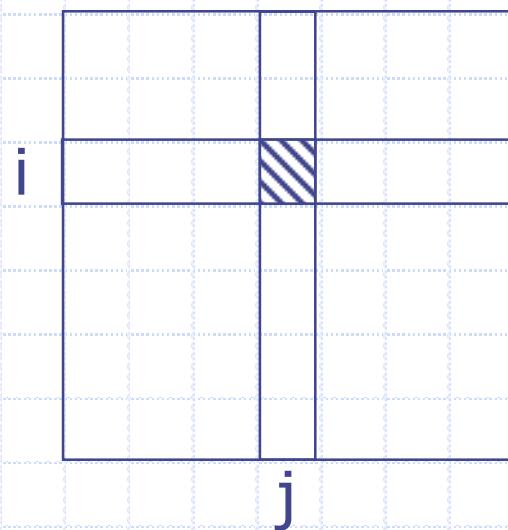
- Extrema du gradient (f')
- Passages par zéro du Laplacien (f'')

⑤ Filtrage linéaire

Filtres passe-haut: Gradients

$$g_h(i, j) = \frac{1}{2} [f(i+1, j) - f(i-1, j)] \longrightarrow [-\frac{1}{2} \ 0 \ \frac{1}{2}]$$

$$g_v(i, j) = \frac{1}{2} [f(i, j+1) - f(i, j-1)] \longrightarrow \begin{bmatrix} -\frac{1}{2} \\ 0 \\ \frac{1}{2} \end{bmatrix}$$



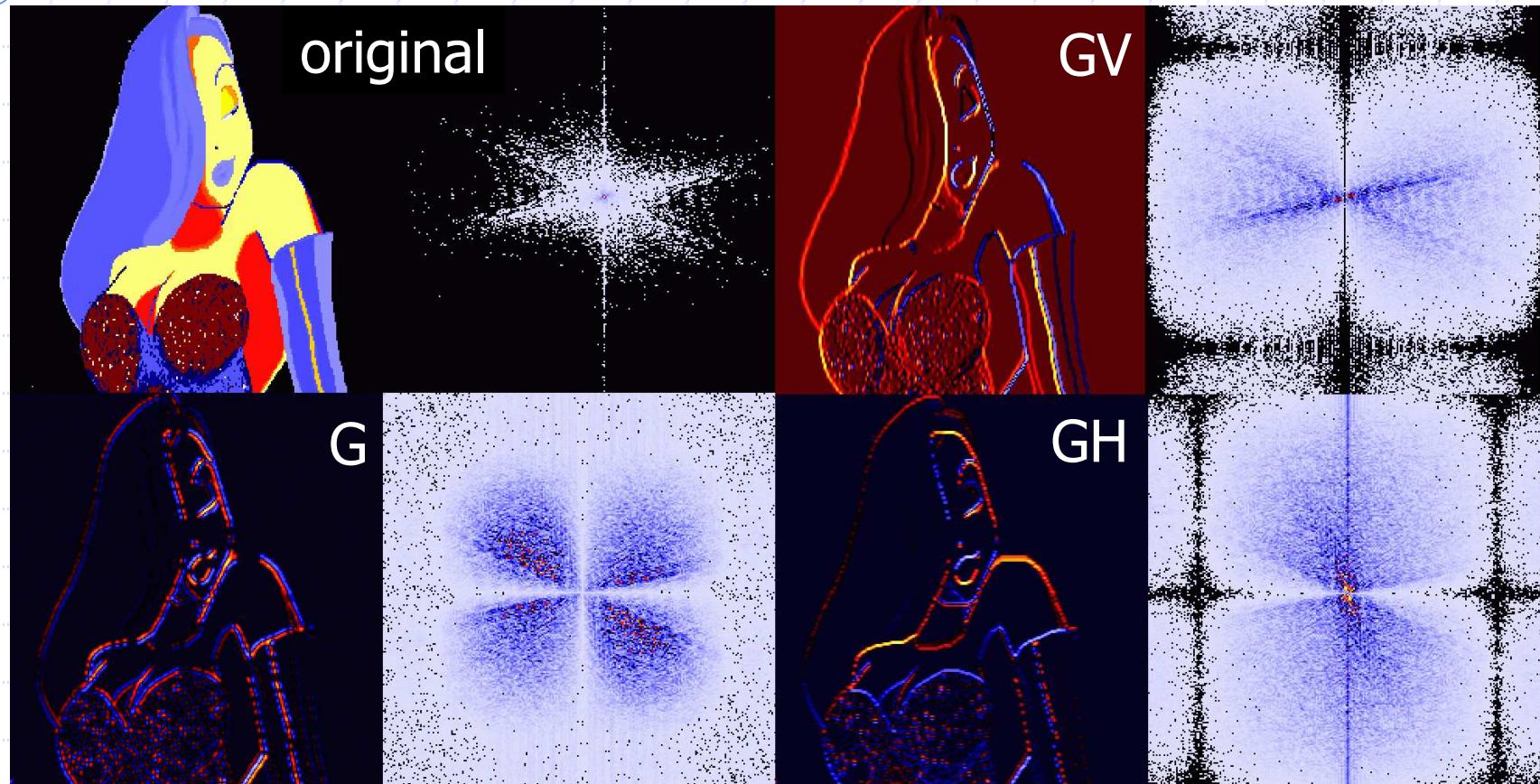
Généralisation 2d:

$$G_h = \begin{bmatrix} -1 & 0 & 1 \\ -\sqrt{2} & 0 & \sqrt{2} \\ -1 & 0 & 1 \end{bmatrix}$$

$$G_v = \begin{bmatrix} -1 & -\sqrt{2} & -1 \\ 0 & 0 & 0 \\ 1 & \sqrt{2} & 1 \end{bmatrix}$$

⑤ Filtrage linéaire

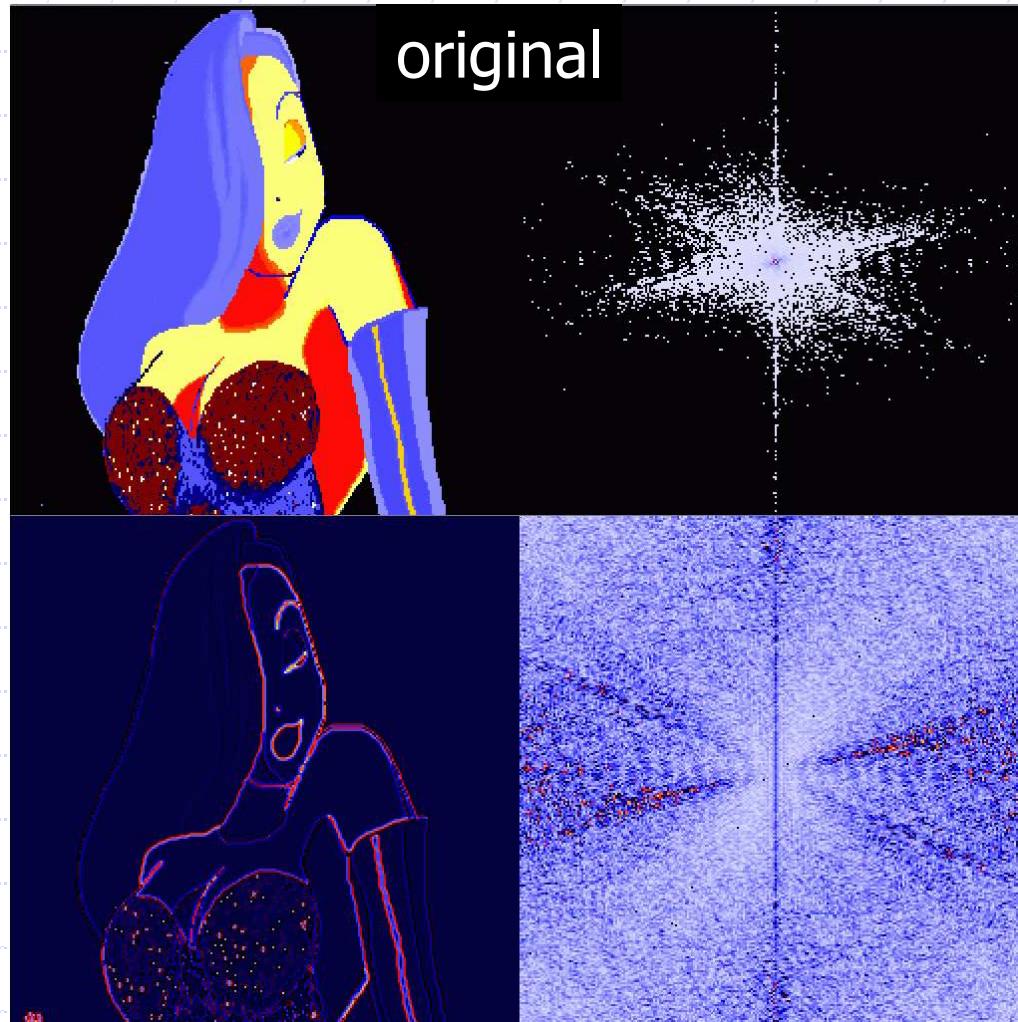
Filtres passe-haut: Gradients



GH (GV) efface les frontières verticales (horizontales)

⑤ Filtrage linéaire

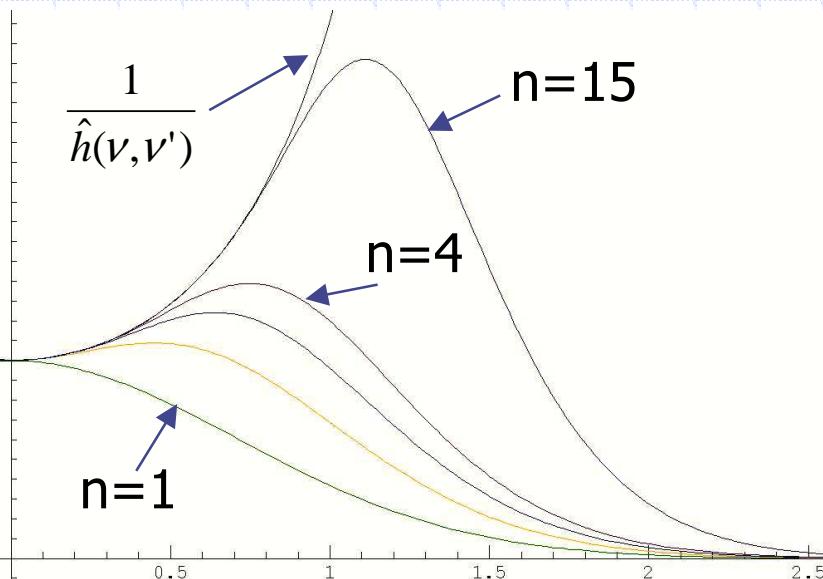
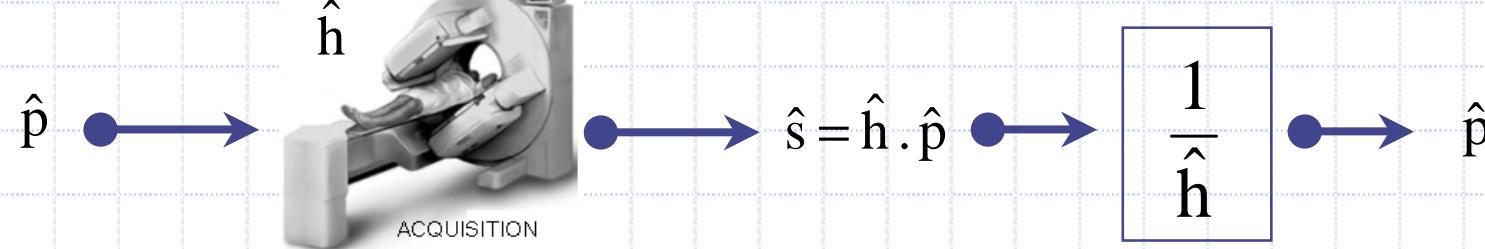
Filtres passe-haut: Laplacien



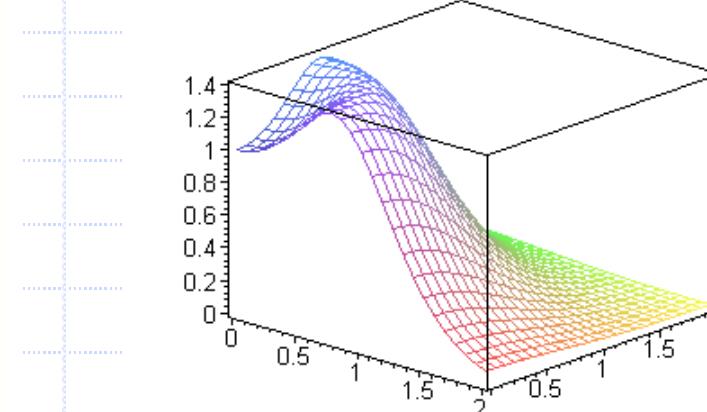
$$\begin{bmatrix} 1 & 1 & 1 \\ 1 & -8 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

⑤ Filtrage linéaire

Filtre de déconvolution de Metz



$$\hat{m}(v, v') = \frac{1 - [1 - h(v, v')]^n}{h(v, v')}$$



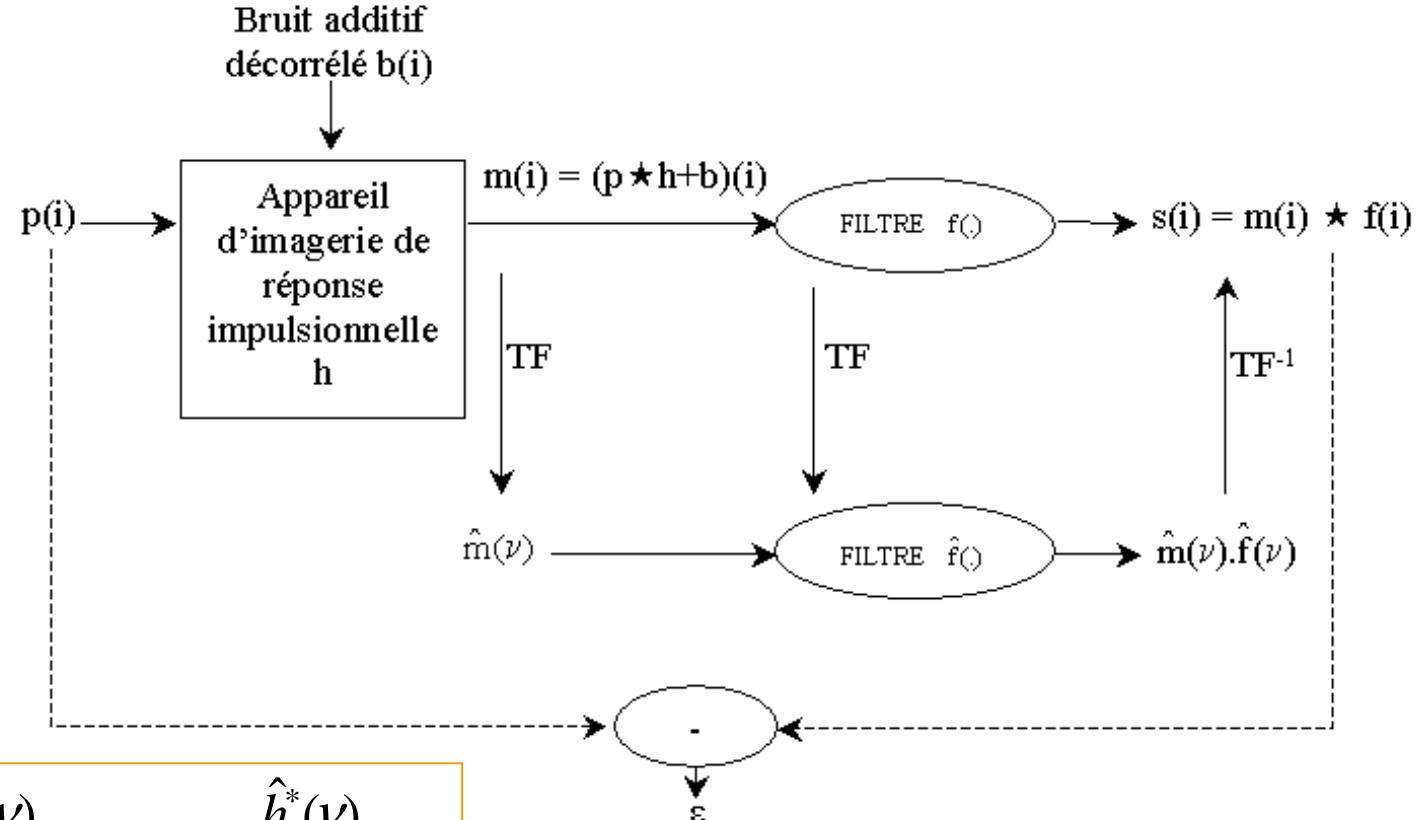
$$n = 0.834 \cdot \ln(C) - 7.774$$

King et al. *JNM* 83;24

Metz Et al. *JNM* 73; 15

⑤ Filtrage linéaire

Filtre de déconvolution de Wiener



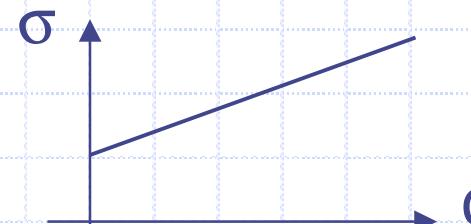
$$\hat{f}(v) = \frac{\hat{h}^*(v)}{|\hat{h}(v)|^2 + \frac{S_b(v)}{S_p(v)}} \approx \frac{\hat{h}^*(v)}{|\hat{h}(v)|^2 + \frac{|\hat{b}(v)|^2}{|\hat{p}(v)|^2}}$$

$$\hat{h}=1 \Rightarrow \hat{f}(v) = \frac{S_p(v)}{S_p(v)+S_b(v)} = \frac{S_m(v)-S_b(v)}{S_m(v)} = 1 - \frac{S_b(v)}{S_m(v)} \rightarrow 0$$

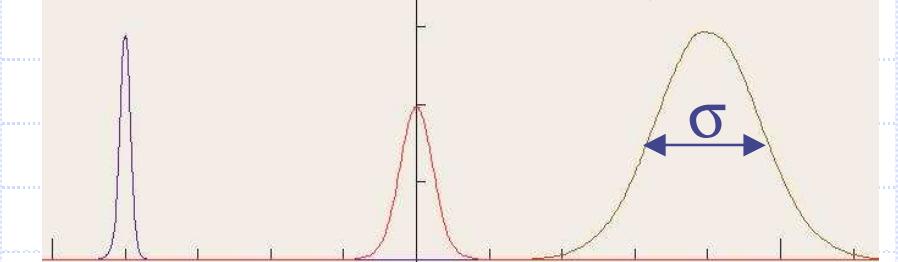
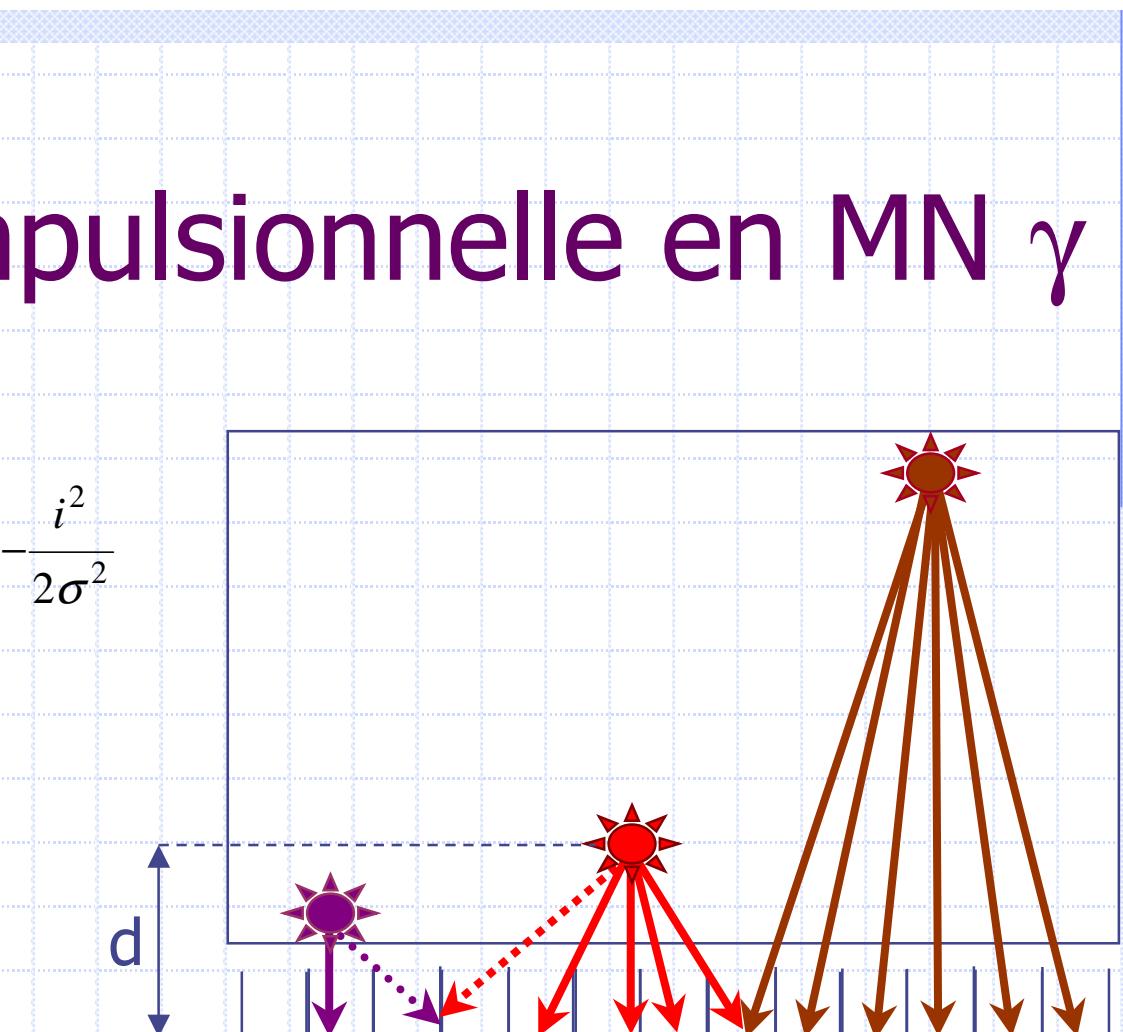
Réponse impulsionnelle en MN γ

◆
$$h(i) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{i^2}{2\sigma^2}}$$

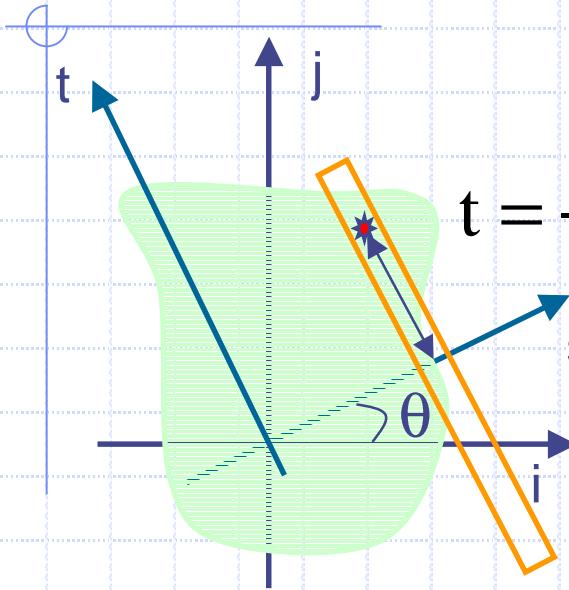
◆
$$\sigma = k.d + k'$$



d



Relation fréquence-distance

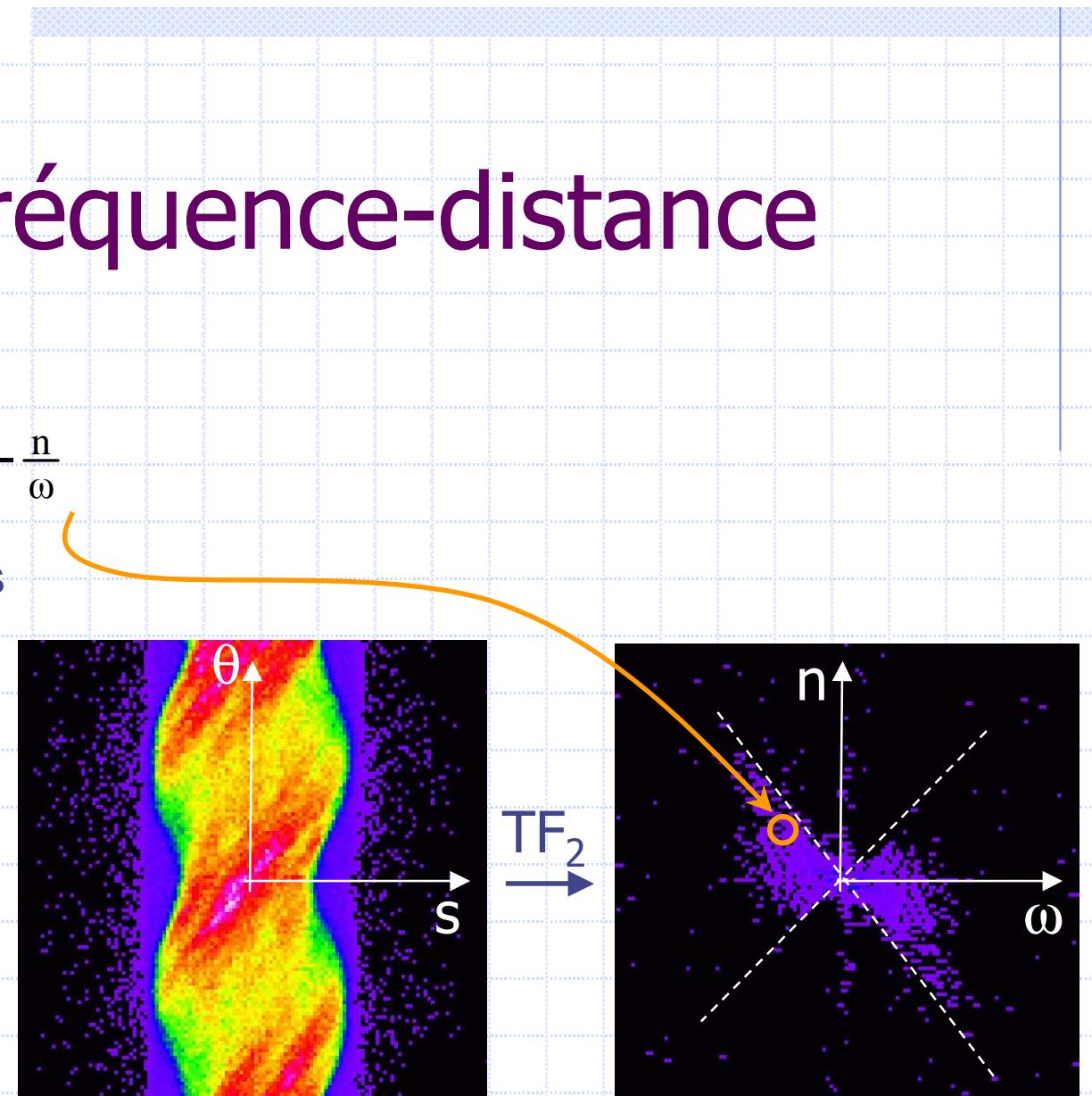


Une désintégration contribue à

$$\hat{p}_c(\omega, n)$$

quand θ permet que

$$t = -\frac{n}{\omega}$$

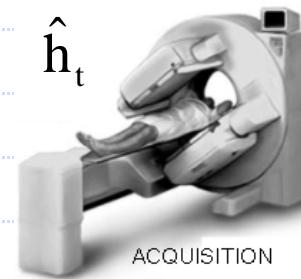


$$p_c(s, \theta) = \int f(i, j) dt$$

$$\hat{p}_c(\omega, n)$$

Déconvolution en TEMP

$$\hat{p}$$



\hat{h}_t

$$h_t(i) = \frac{1}{\sqrt{2\pi}\sigma_t} e^{-\frac{i^2}{2\sigma_t^2}}$$

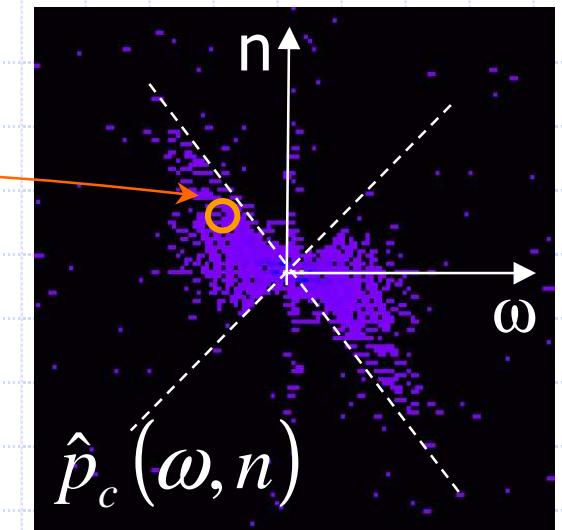
$$\hat{p}_c = \hat{h}_t \cdot \hat{p}$$

$$\frac{1}{\hat{h}_t}$$

$$\hat{p}$$

$$\hat{p}_c(\omega, n) = \hat{h}_{-\frac{n}{\omega}}(\omega) \cdot \hat{p}(\omega, n)$$

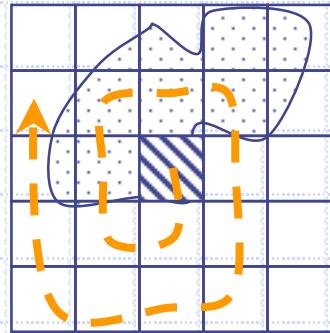
$$\hat{p}(\omega, n) = \frac{1}{\hat{h}_{-\frac{n}{\omega}}(\omega)} \cdot \hat{p}_c(\omega, n)$$



Edholm, Lewitt et al. Proc SPIE 1986, et IEEE-TMI, 1989

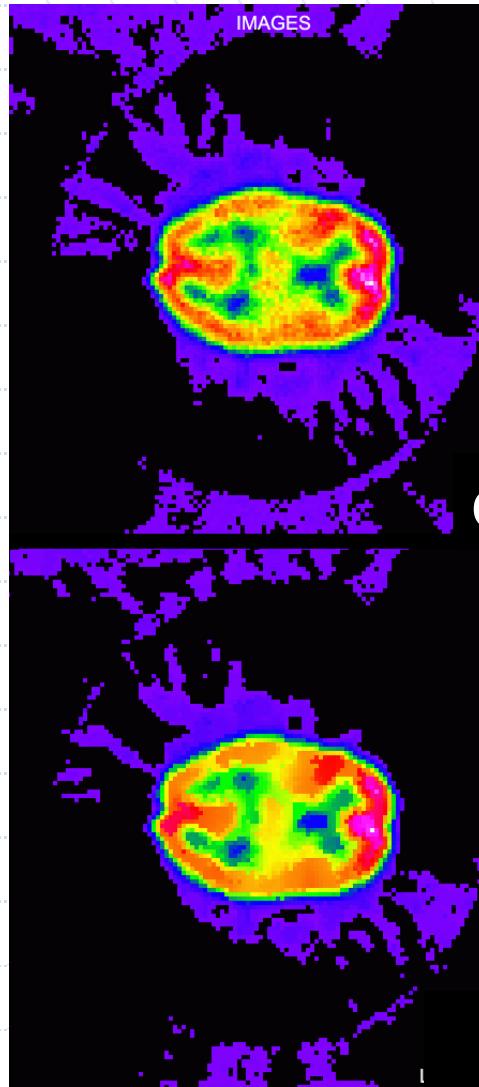
⑥ Filtrage non linéaire

Lissage sur masque adapté (VSS)



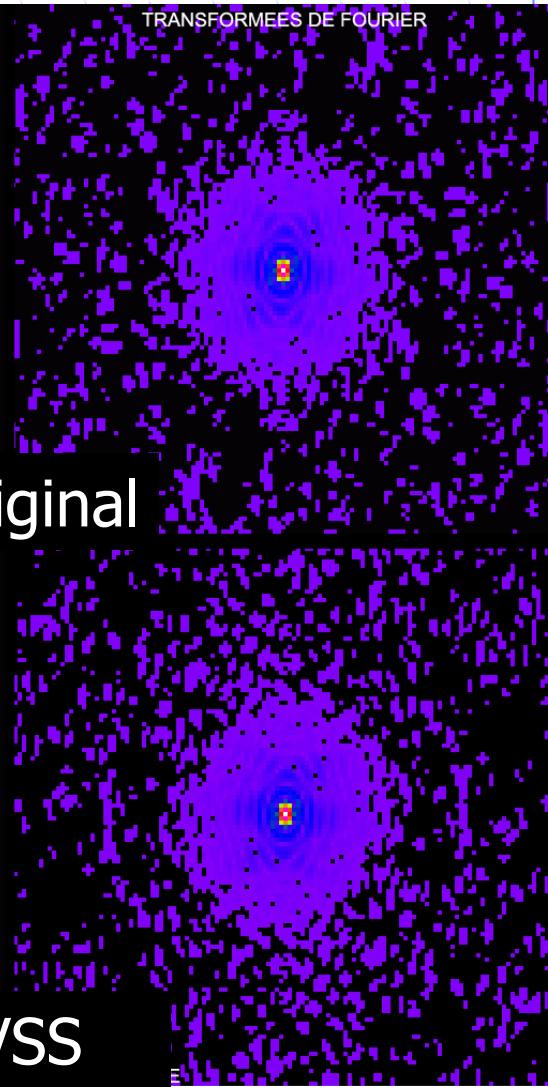
Accumulation pour
moyenne des

$$s(i',j') \in s(i,j) \pm 2\sqrt{s(i,j)}$$



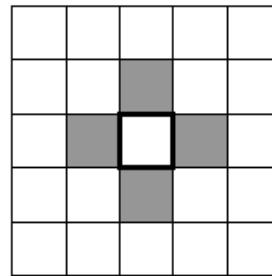
original

VSS

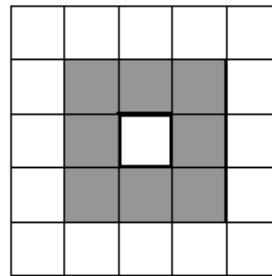


⑥ Filtrage non linéaire

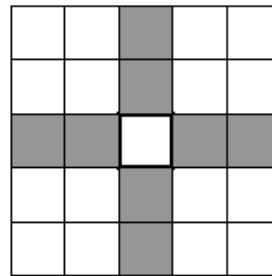
Filtre médian



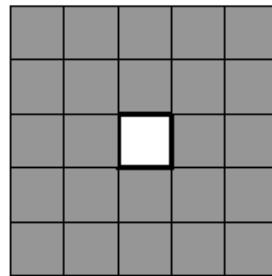
Connexité 4



Connexité 8



Connexité 4

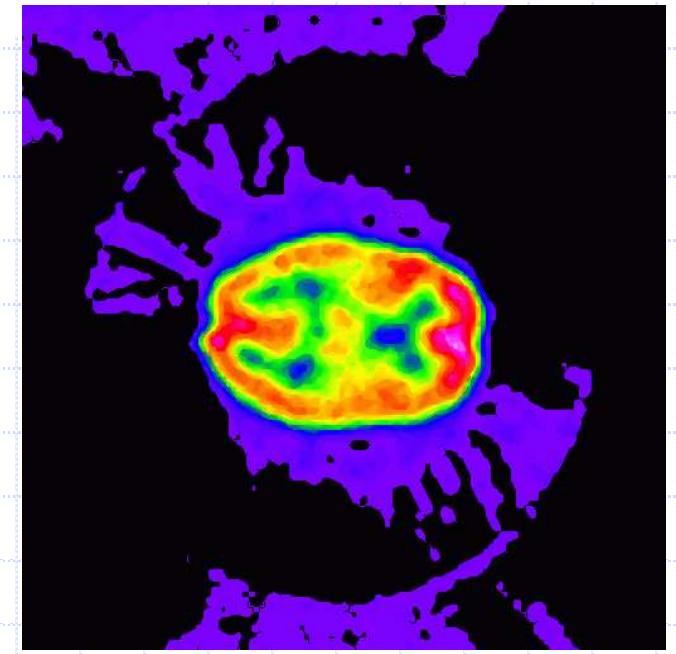


Connexité 8

Taille 1

Taille 2

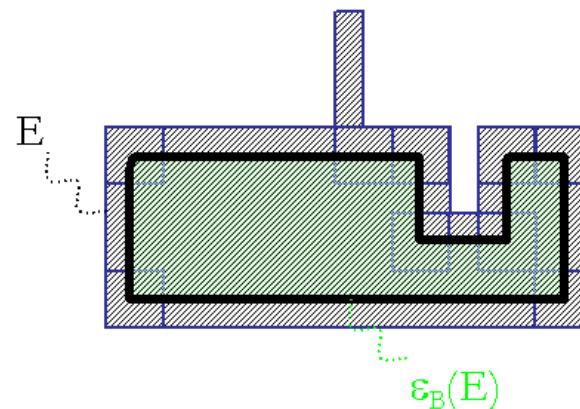
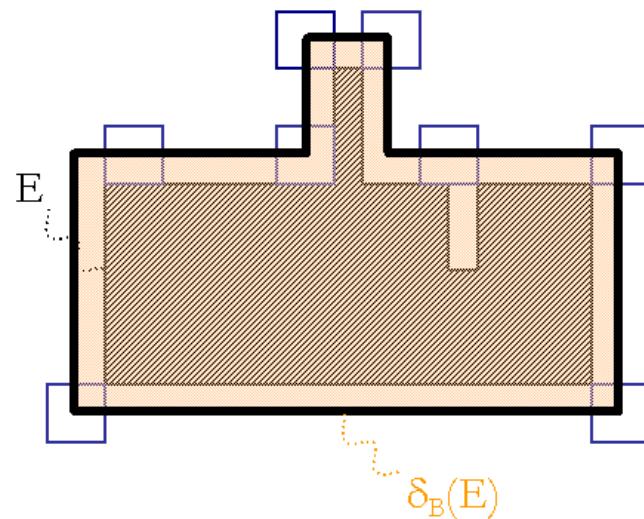
On remplace $s(i,j)$ par le NG médian dans un voisinage fixe de (i,j)



⑥ Filtrage non linéaire

Opérateurs de Minkowski

Élément structurant centré en x



$$\begin{aligned}\delta_B(E) &= \{\text{centres } X / B_X \cap E \neq \emptyset\} \\ &= \cup \{B_X, X \in E\}\end{aligned}$$

$$\varepsilon_B(E) = \{\text{centres } X / B_X \subset E\}$$

$$\varepsilon_B(E) = [\delta_B(E^c)]^c$$

Filtres morphologiques

ψ est un filtre morphologique si et seulement si:

◆ $\psi \circ \psi = \psi$

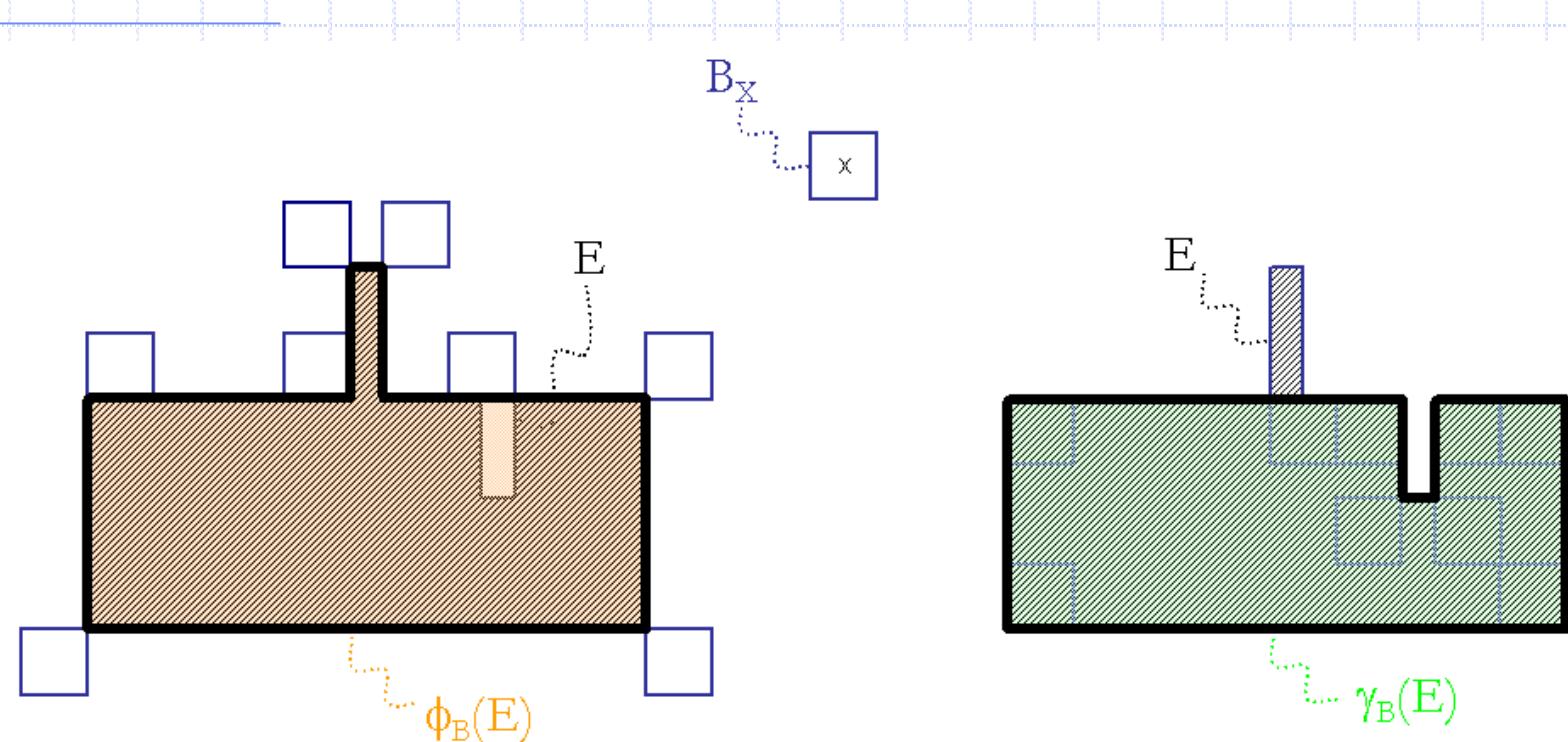
- Modifie une fois pour toute certaines caractéristiques

◆ pour tout ensembles A et B, $A \subset B \Rightarrow \psi(A) \subset \psi(B)$

- Respecte les relations contenant/contenu

⑥ Filtrage non linéaire

Ouvertures et fermetures binaires

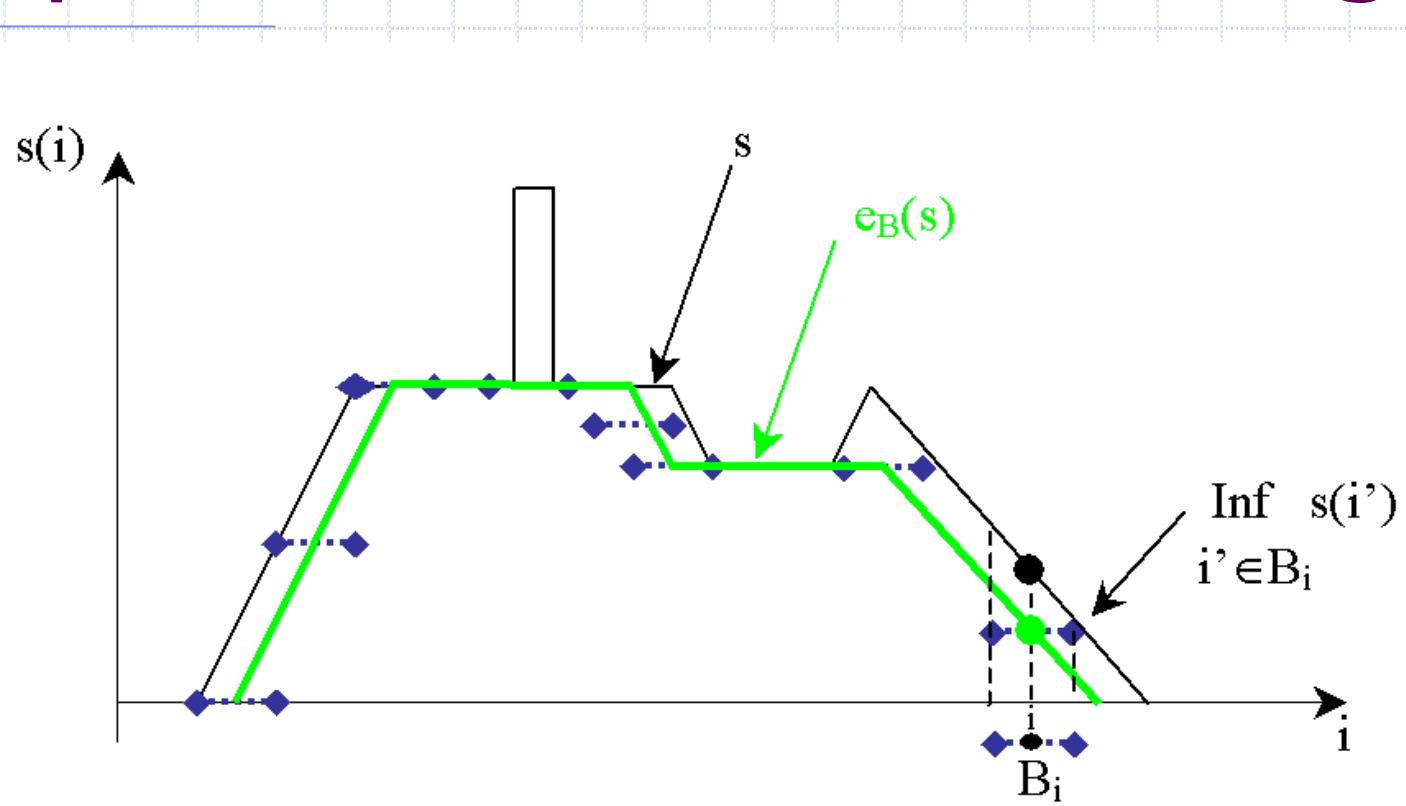


$$\begin{aligned}\phi_B(E) &= (\varepsilon \circ \delta)(E) = \varepsilon[\delta(E)] \\ &= \cup \{ B_X / B_X \cap X = \emptyset \}^c\end{aligned}$$

$$\begin{aligned}\gamma_B(E) &= (\delta \circ \varepsilon)(E) = \delta [\varepsilon(E)] \\ &= \cup \{ B_X / B_X \subset X \}\end{aligned}$$

⑥ Filtrage non linéaire

Opérateurs en niveaux de gris

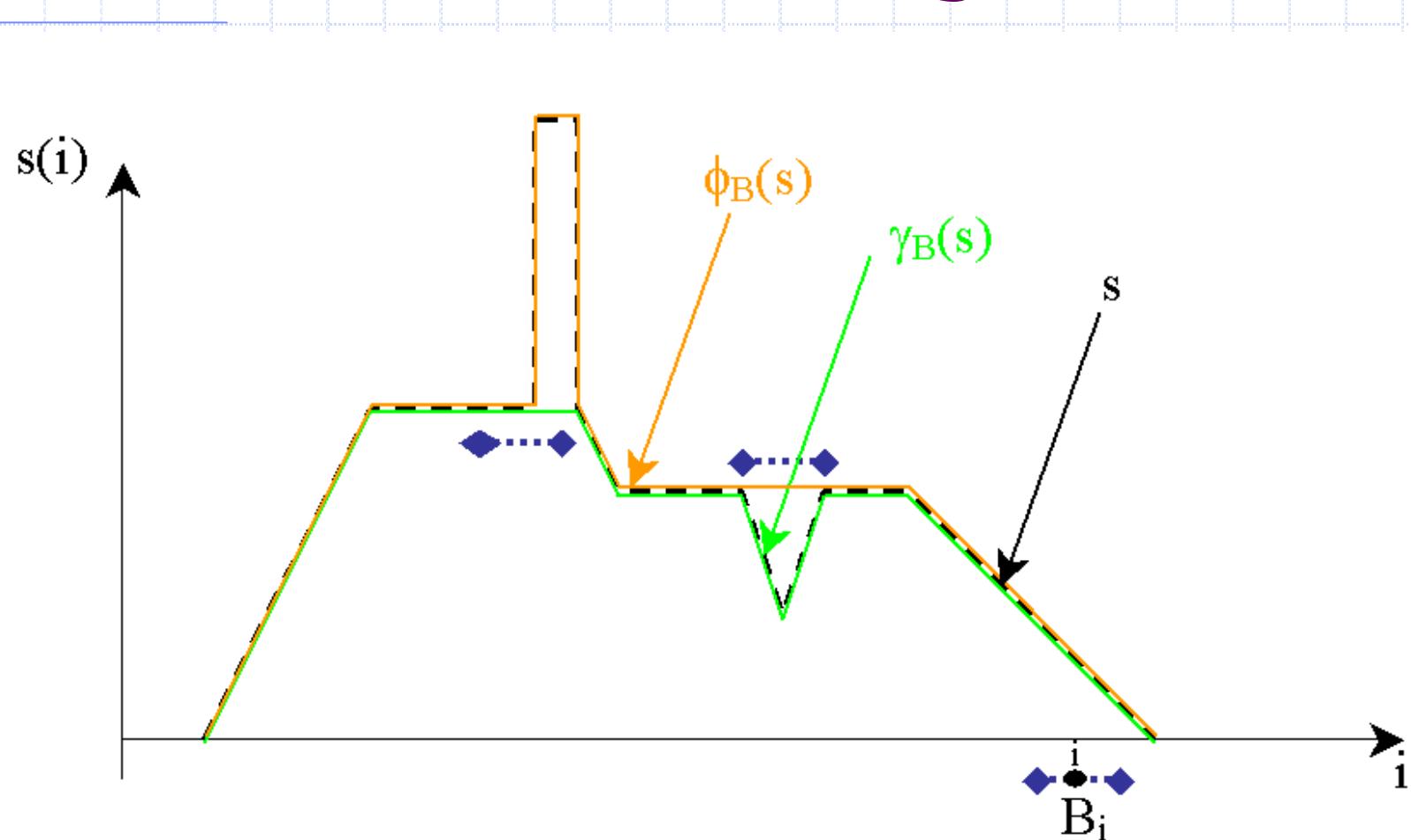


$$\mathcal{E}_B(s)(i, j) = \inf_{(i', j') \in B_{i,j}} s(i', j')$$

$$\delta_B(s)(i, j) = \sup_{(i', j') \in B_{i,j}} s(i', j')$$

⑥ Filtrage non linéaire

Filtres en niveaux de gris

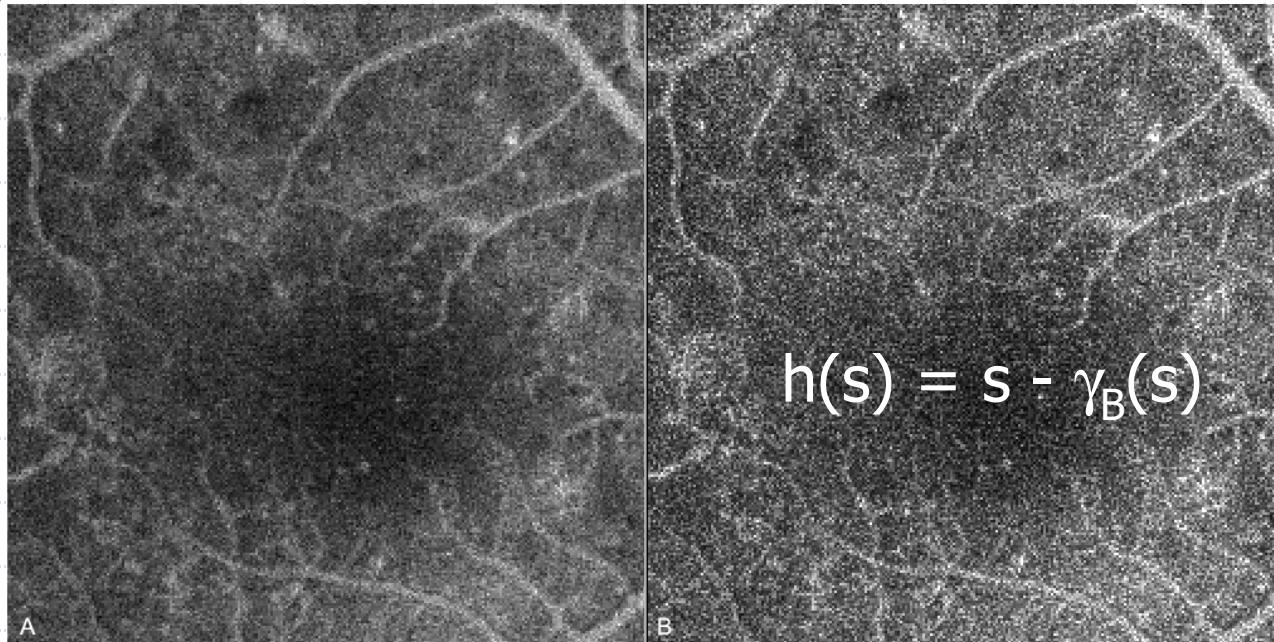


$$\phi_B(s) = \varepsilon[\delta(s)]$$

$$\gamma_B(s) = \delta[\varepsilon(s)]$$

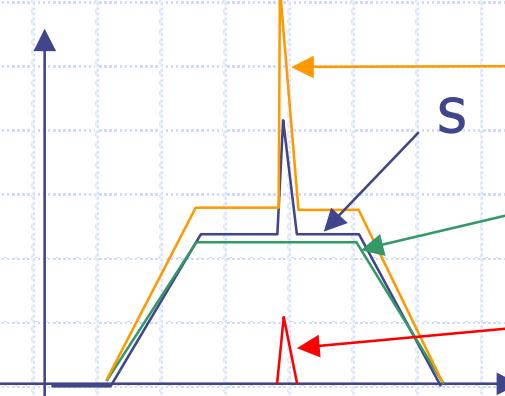
⑥ Filtrage non linéaire

Top hat transform



original

$$h(s)=s-\gamma(s)$$



$$\gamma(s)$$

$$s-\gamma(s)$$

Opérateurs géodésiques

$$\Delta_s(m) = \wedge[\delta_B(m), s], \quad \text{où } m \leq s$$

$$E_s(m) = \vee[\varepsilon_B(m), s], \quad \text{où } m \geq s$$

$$\gamma^{\text{rec}}(s) = \Delta_s^\infty(m)$$

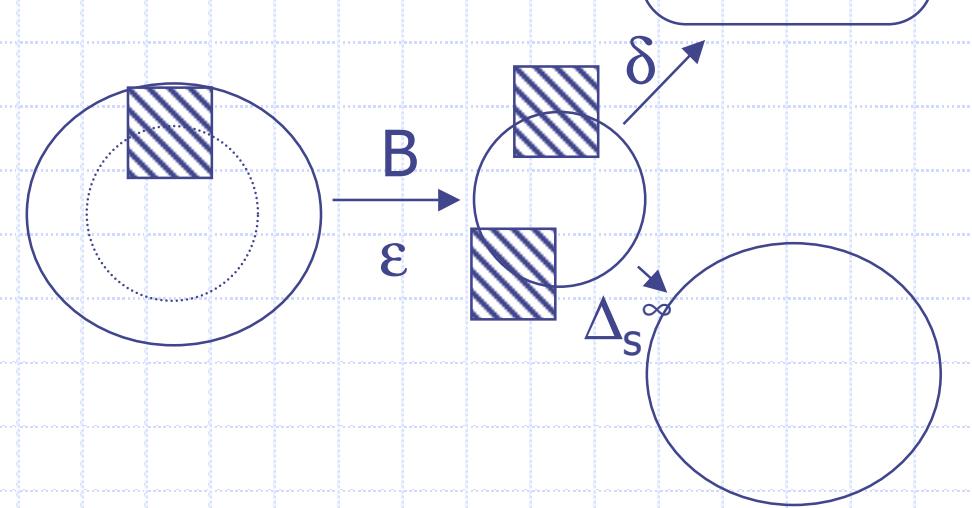
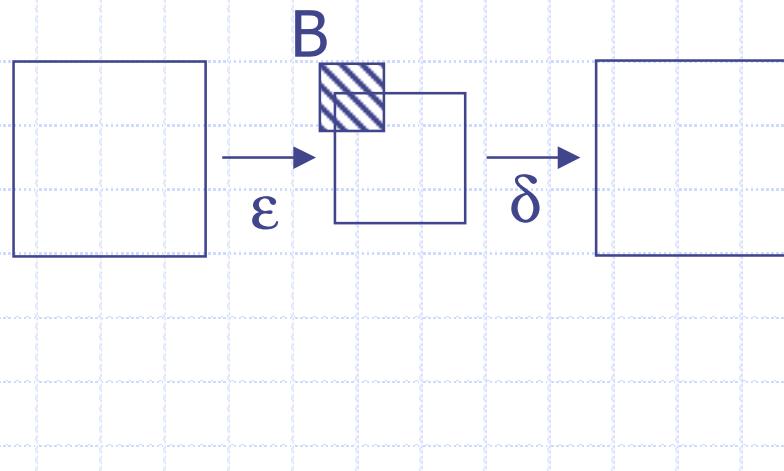
$$\varphi^{\text{rec}}(s) = E_s^\infty(m)$$

⑥ Filtrage non linéaire

Érosion (dilatation)-reconstruction

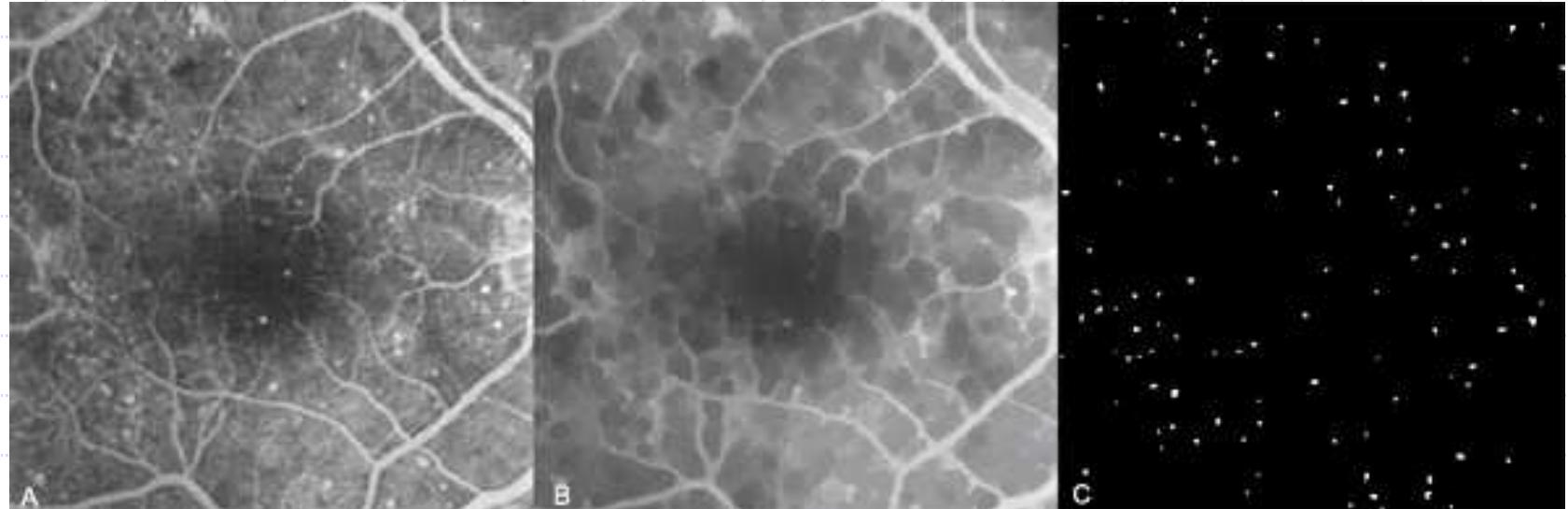
$$\gamma^{\text{rec}}(s) = \Delta_s^\infty(\varepsilon_B(s))$$

$$\varphi^{\text{rec}}(s) = E_s^\infty(\varphi_B(s))$$



⑥ Filtrage non linéaire

Érosion (dilatation)-reconstruction



original

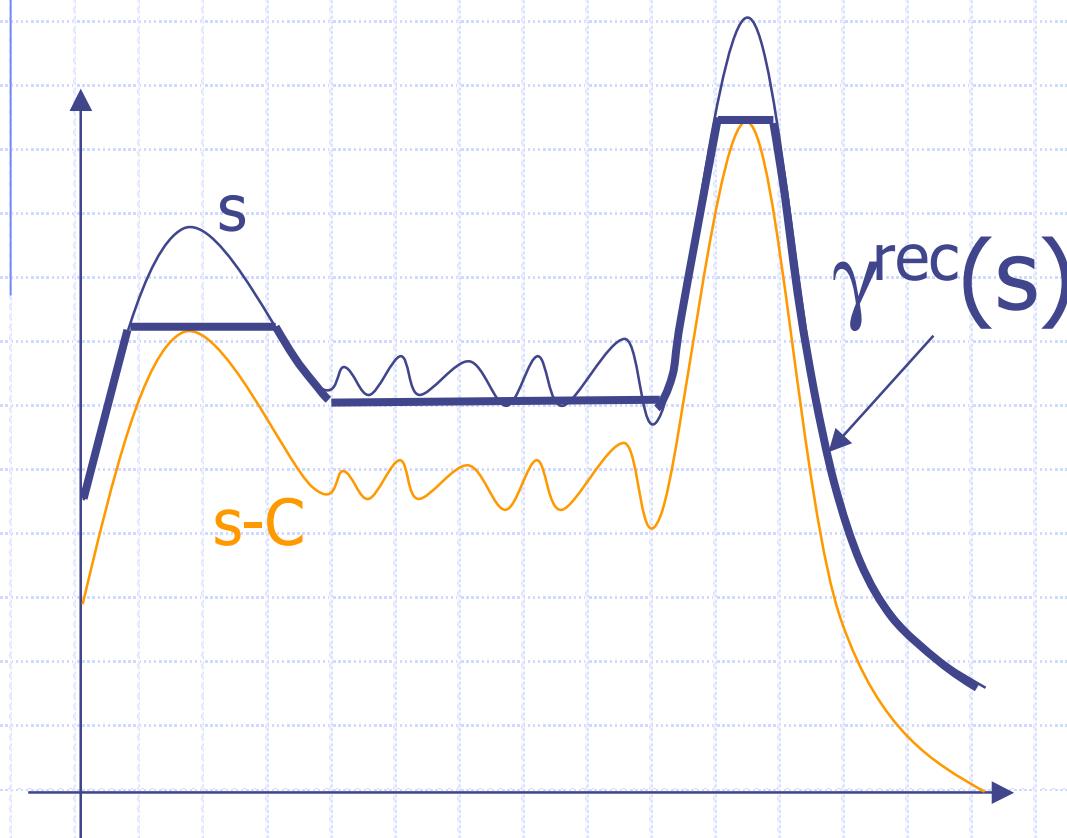
$$\gamma^{\text{rec}}(s) = \Delta_S^\infty(\varepsilon_B(s))$$

seuil

$$\phi^{\text{rec}}(s) = E_S^\infty(\delta_B(s))$$

Ouverture de contraste

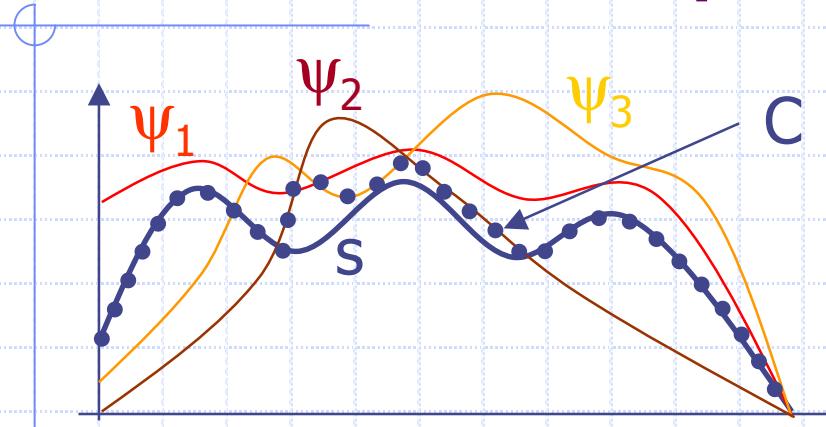
$$\gamma^{\text{rec}}(s) = \Delta^\infty_s(s-C)$$



◆ élimine les composantes de faible contraste

◆ $s - \gamma^{\text{rec}}(s)$ isole les maxima relatifs

Centres morphologiques



◆ Famille de filtres $\{\psi_k\}$

◆ $s(i,j) \leftarrow \wedge_k \psi_k(i,j)$ si $\forall k, \psi_k(i,j) \geq s(i,j)$

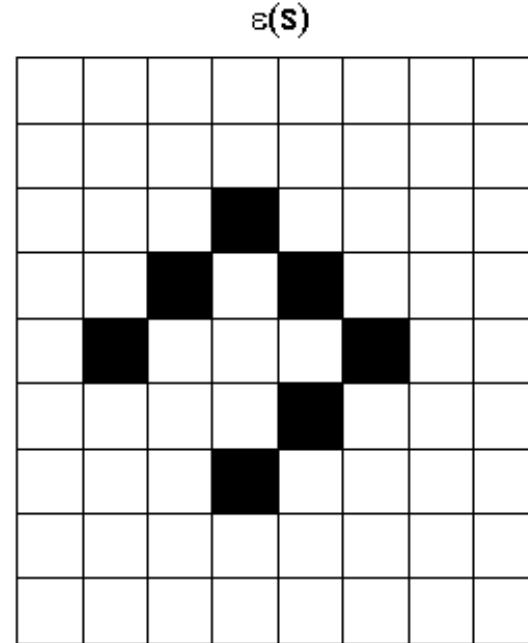
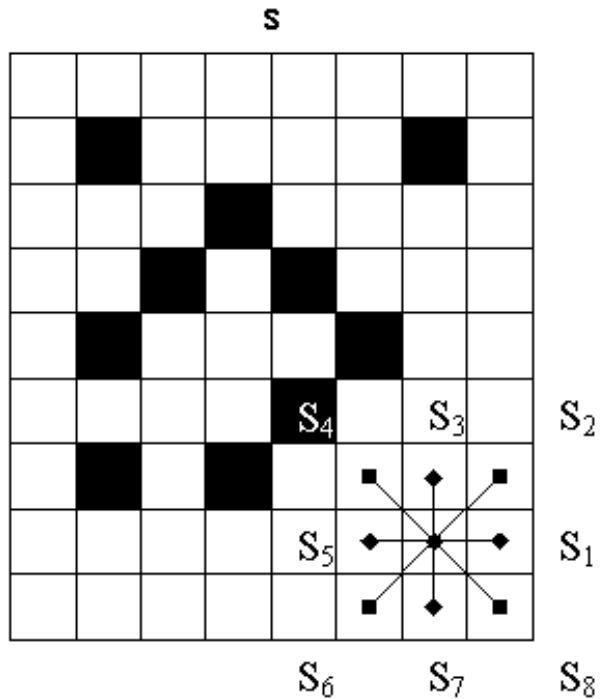
◆ $s(i,j) \leftarrow \vee_k \psi_k(i,j)$ si $\forall k, \psi_k(i,j) \leq s(i,j)$

◆ sinon $s(i,j)$ est inchangée

$$C = (\vee \psi_k) \wedge [I \vee (\wedge \psi_k)] = (\wedge \psi_k) \vee [I \wedge (\vee \psi_k)]$$

⑥ Filtrage non linéaire

Sup et Inf d'opérateurs

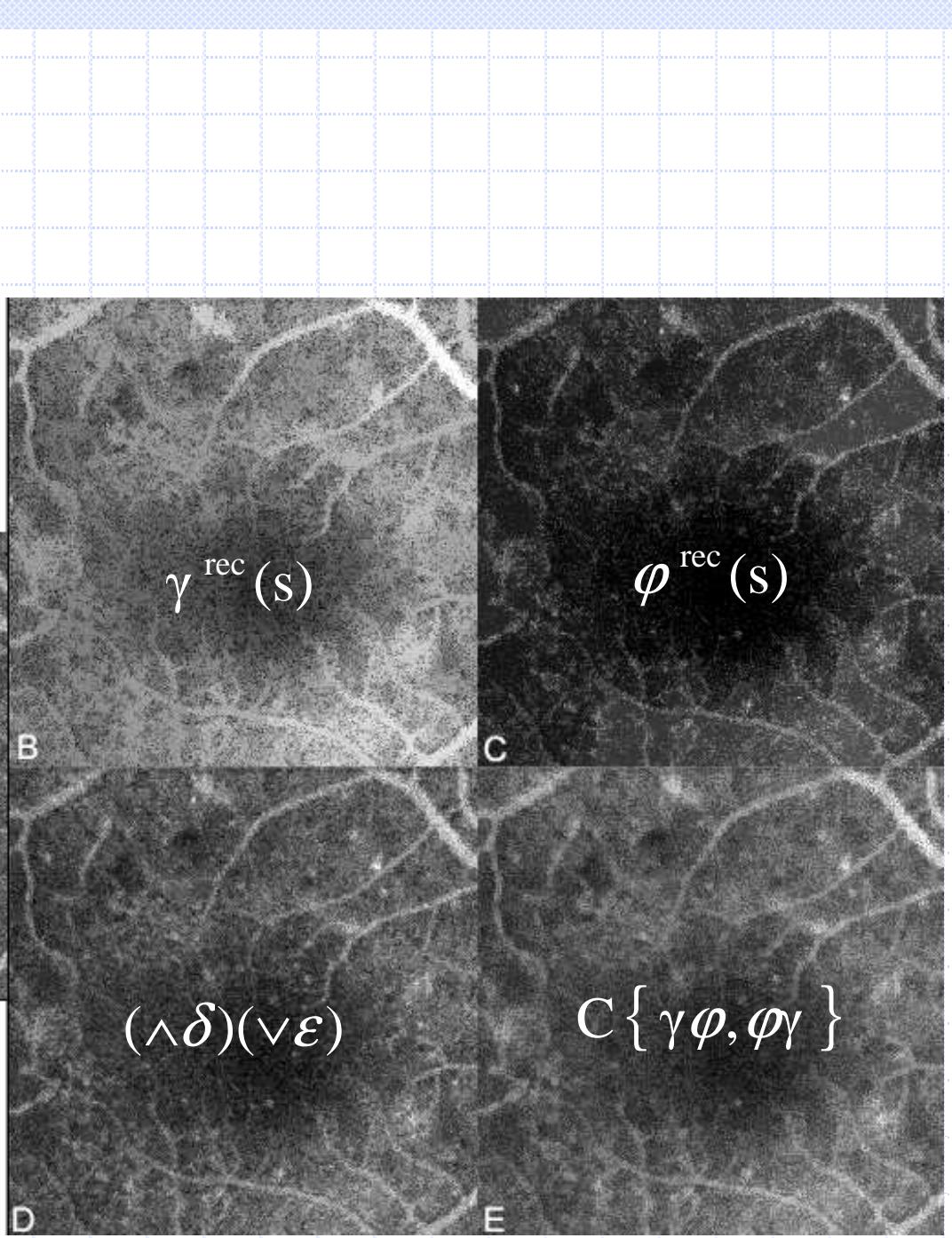
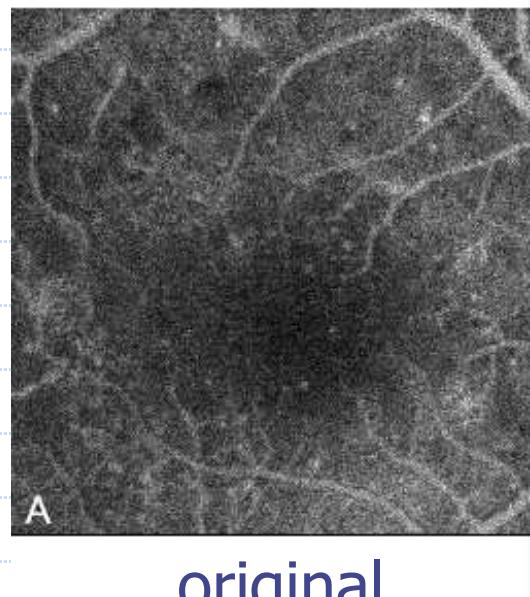


$$\varepsilon(s)(i,j) = \vee_k (\varepsilon_{Sk})(s)(i,j)$$

$$\delta(s)(i,j) = \wedge_k (\delta_{Sk})(s)(i,j)$$

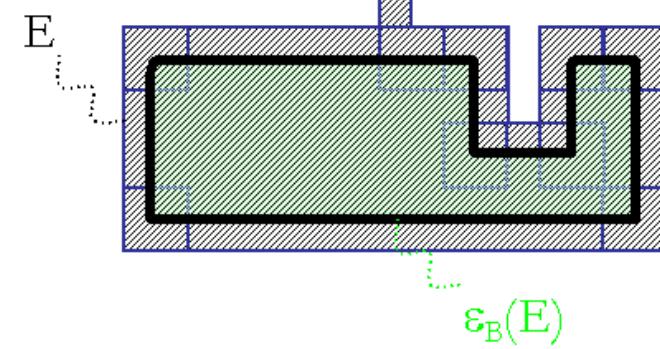
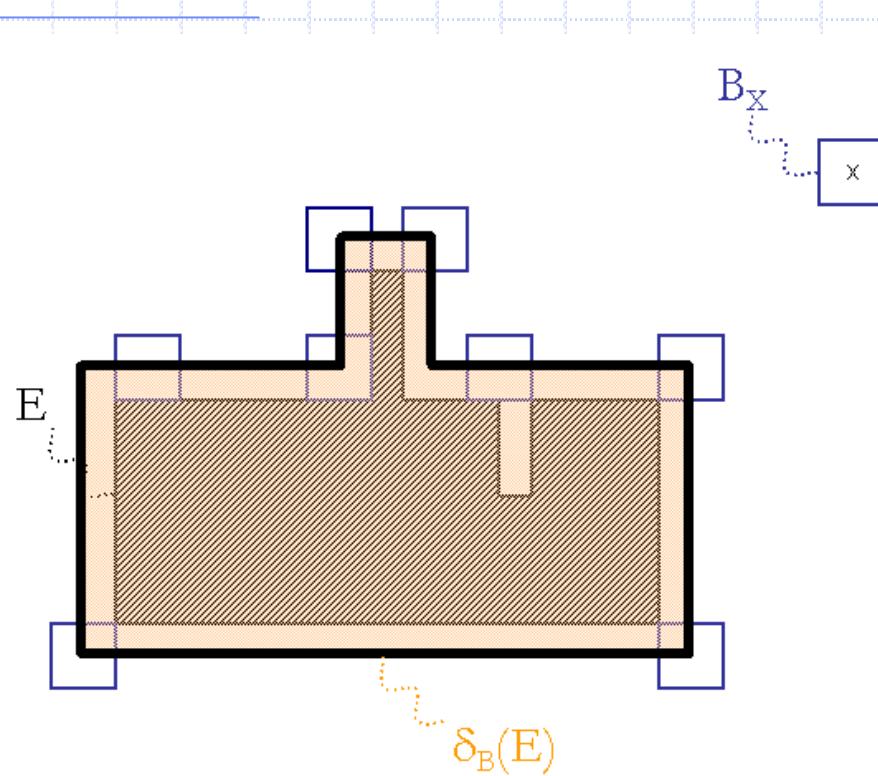
⑥ Filtrage non linéaire

Exemples



⑦ Segmentation morphologique

Gradients morphologiques



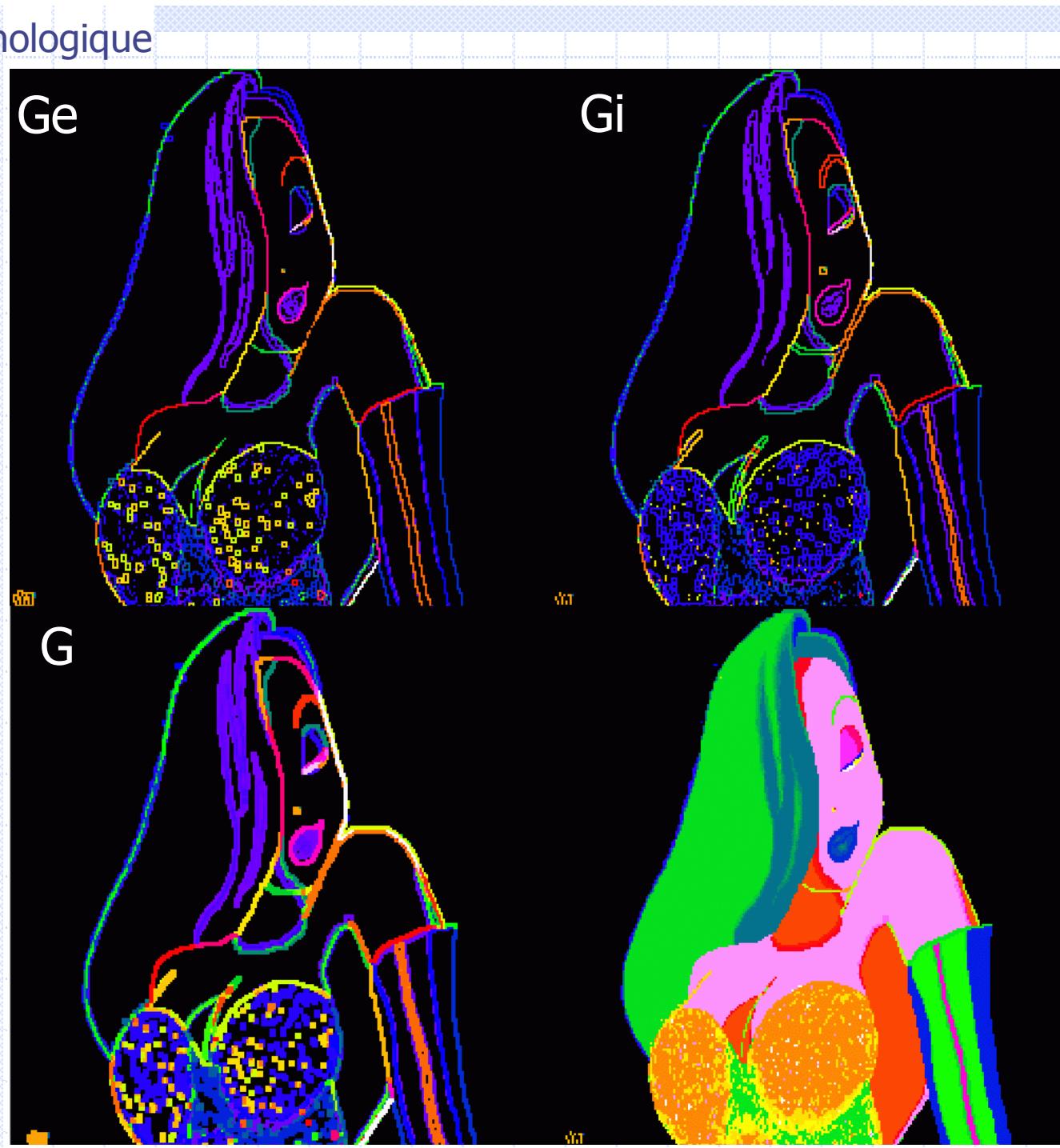
$$G_B^e(f) = \delta_B(f) - f$$

$$G_B^i(f) = f - \varepsilon_B(f)$$

$$G_B^e(f) = \delta_B(f) - \varepsilon_B(f)$$

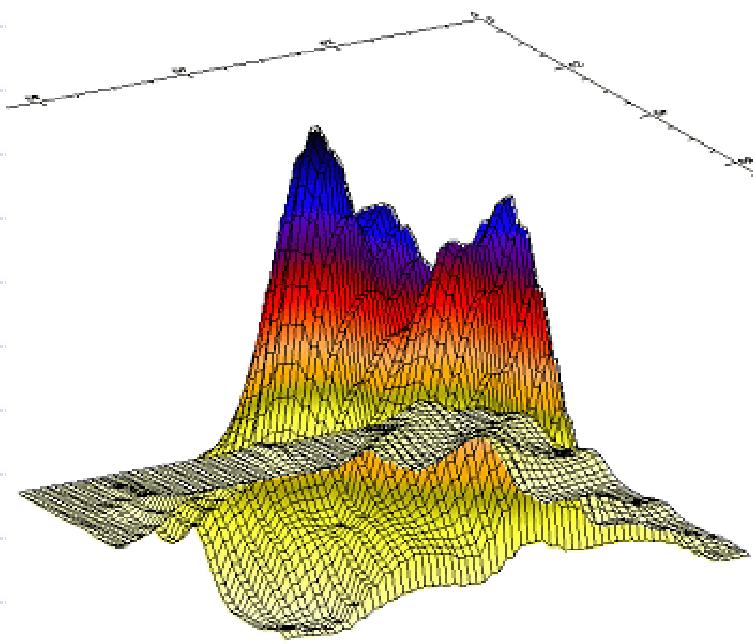
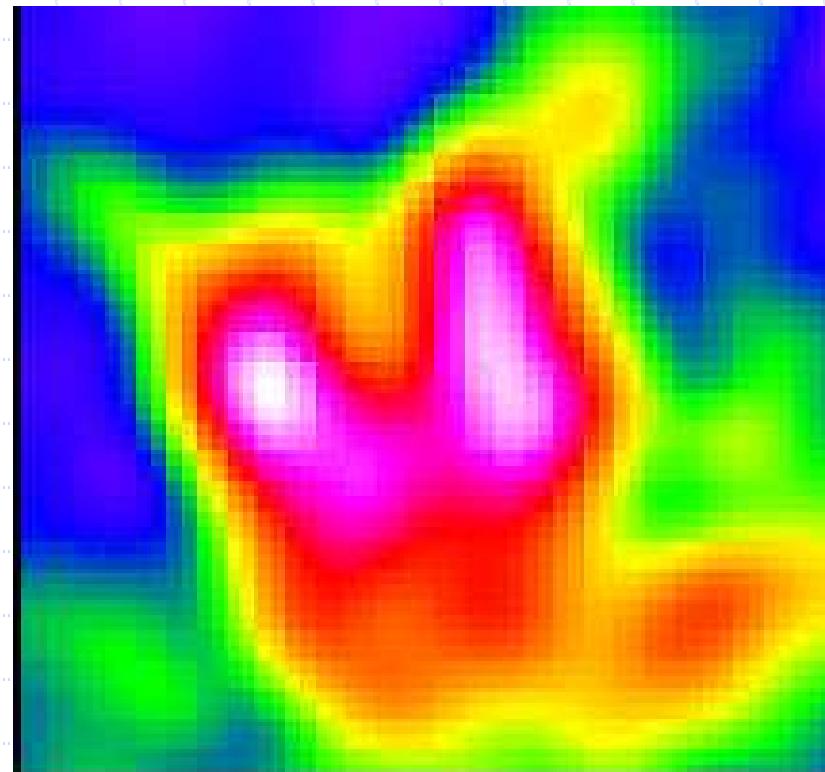
⑦ Segmentation morphologique

Gradients
morpho-
logiques



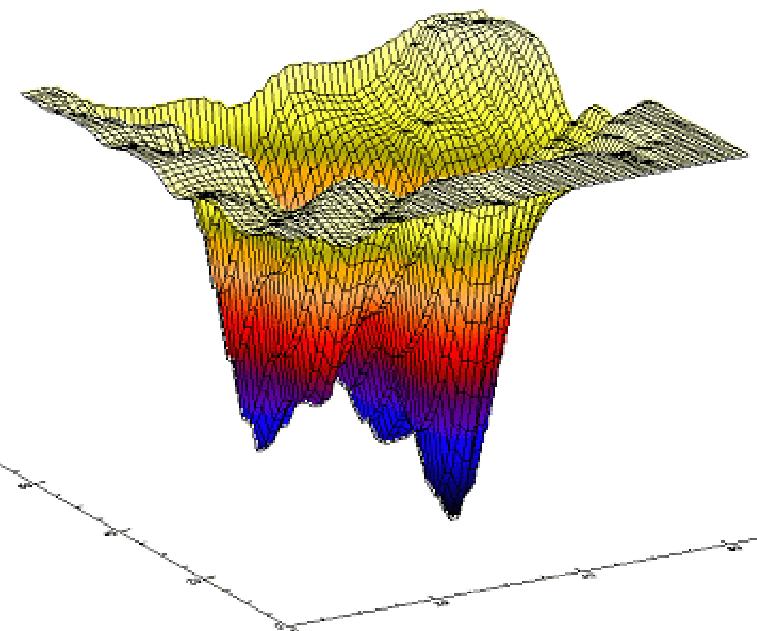
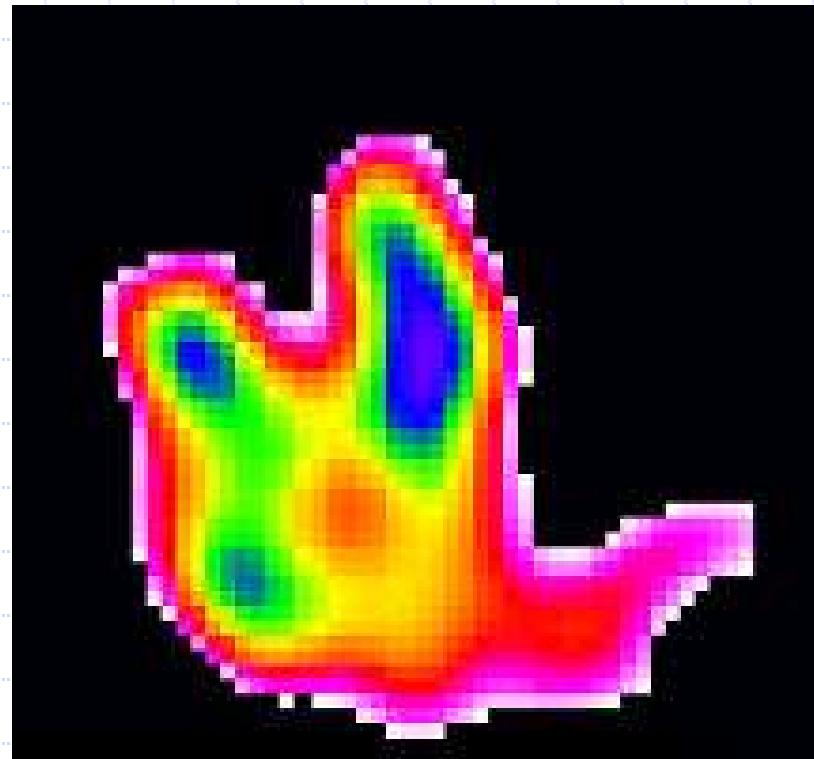
⑦ Segmentation morphologique

Ligne de partage des eaux



⑦ Segmentation morphologique

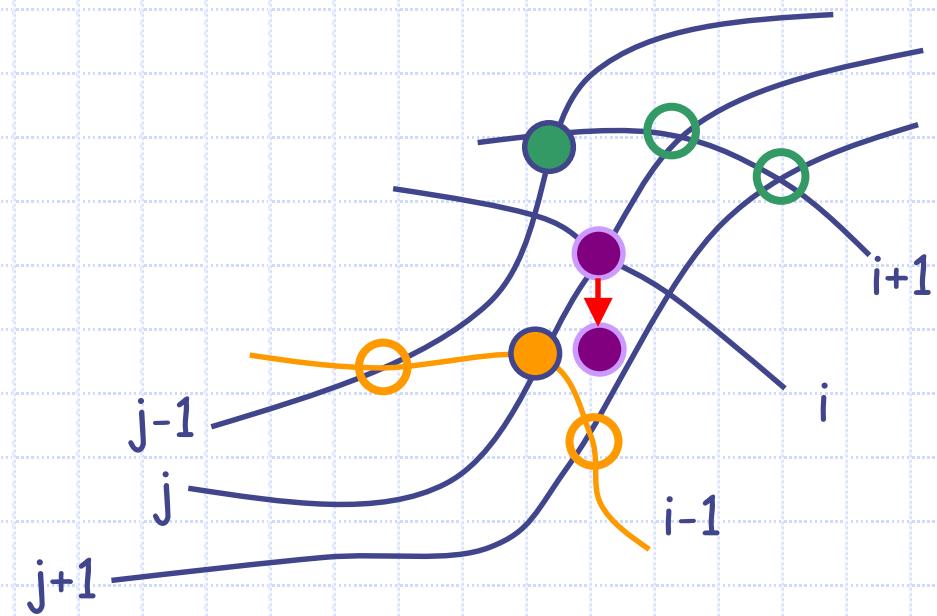
Ligne de partage des eaux



Amincissement homotopique

$$\left(f \circ \begin{bmatrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{bmatrix} \right)(i, j) = f_{\max} \quad \text{si} \quad f_{\max} < f(i, j) \leq f_{\min}$$

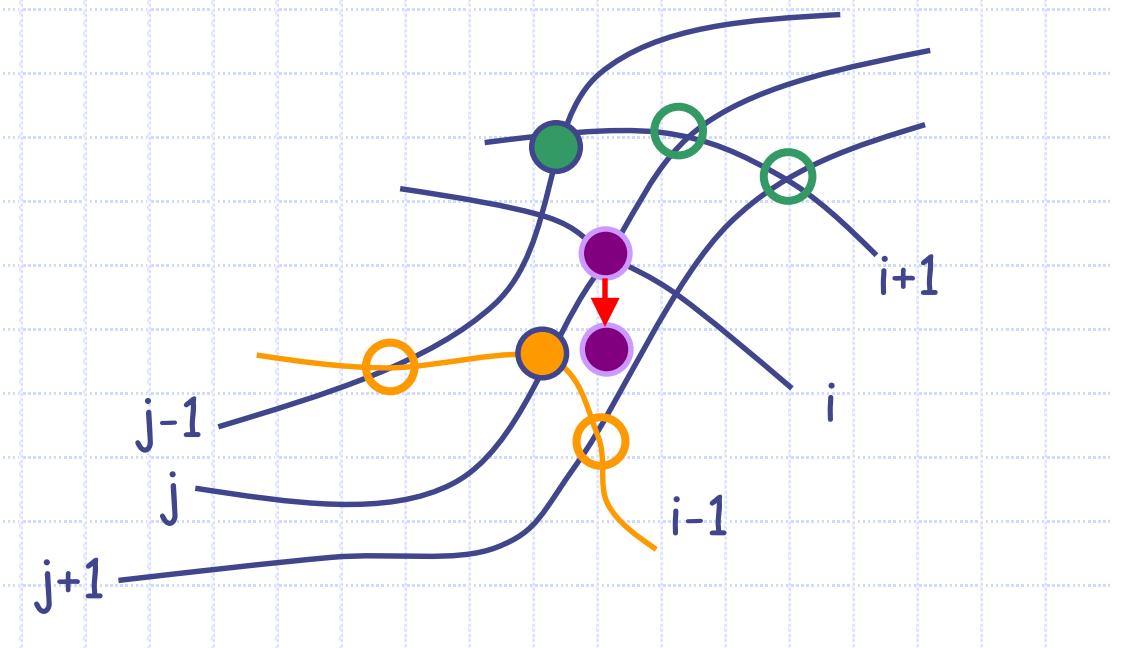
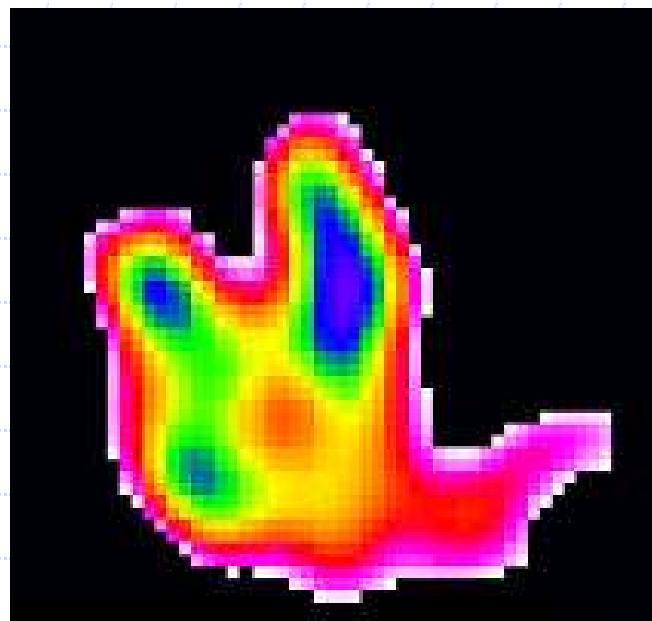
$$L = \begin{bmatrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{bmatrix}$$



⑦ Segmentation morphologique

Amincissement homotopique

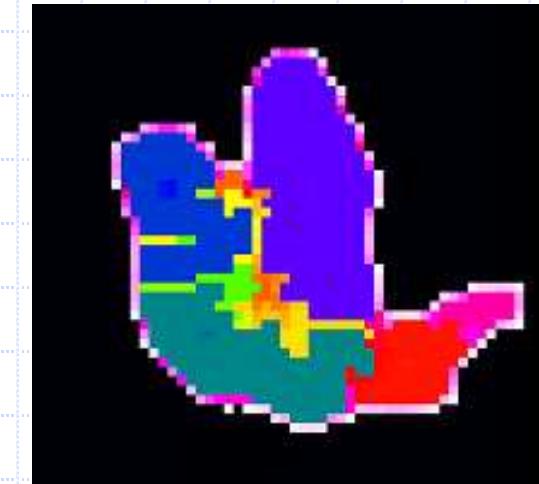
$$\left(f \circ \begin{bmatrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{bmatrix} \right)(i, j) = f_{\max} \quad \text{si} \quad f_{\max} < f(i, j) \leq f_{\min}$$



(Mariano-Goulart et al. EJNM 1998; 22:1300-07 et Revue Acomen 2000;6:69-77)

Ebarbulage par amincissement

$$Sq = (f \circ L_i)^\infty$$

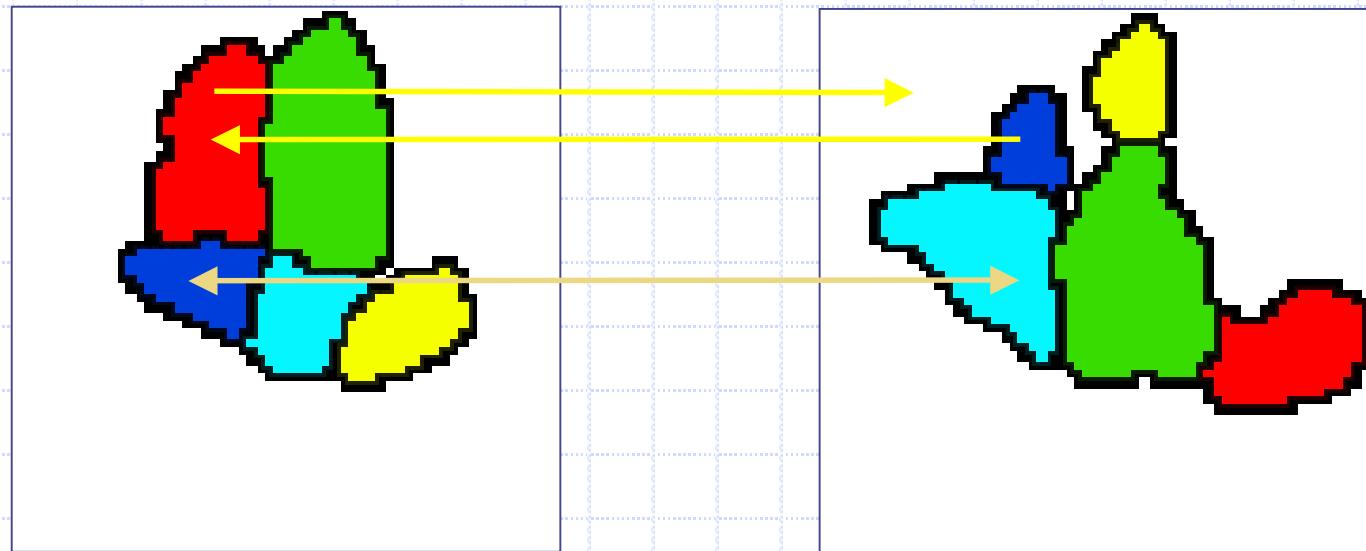


$$LPE = \left(f \circ \begin{bmatrix} 0 & 1 & 0 \\ 1 & -1 & 1 \\ 0 & 0 & 0 \end{bmatrix}_i \right)^\infty$$



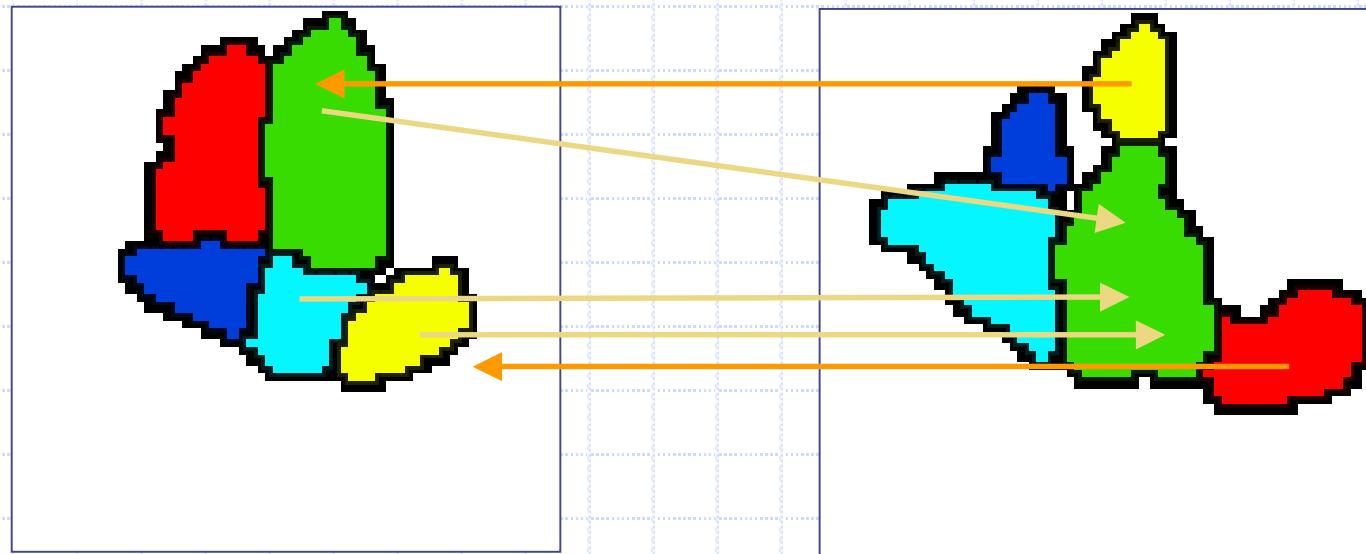
(Mariano-Goulart et al. EJNM 1998; 22:1300-07 et Revue Acomen 2000;6:69-77)

Appariements des ROIs



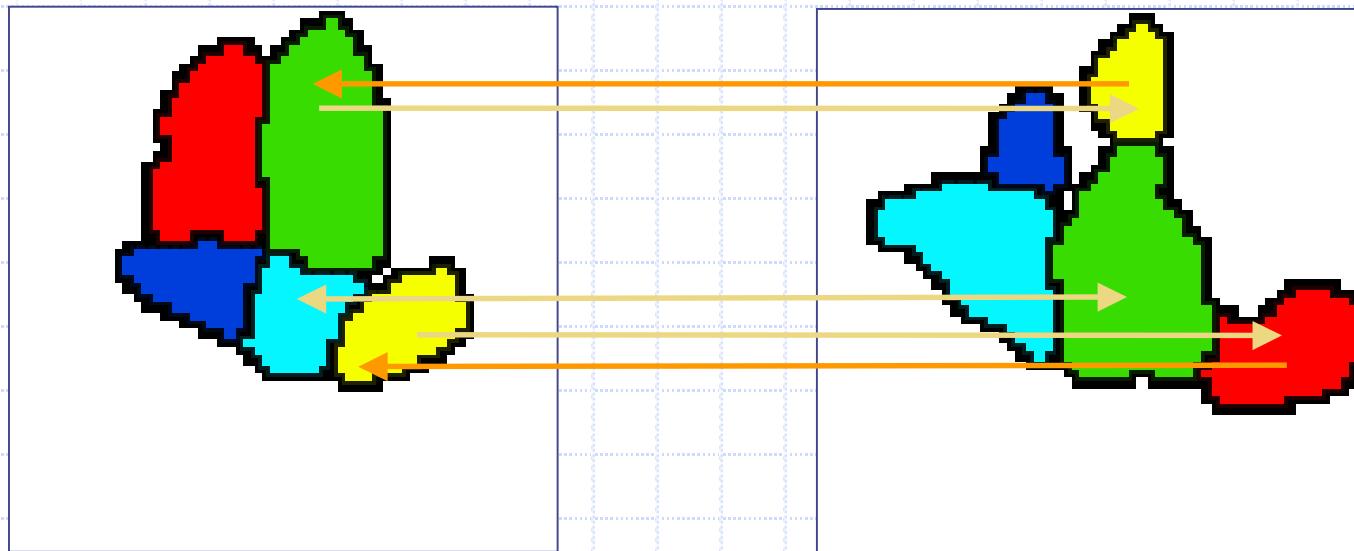
(Mariano-Goulart et al. EJNM 1998; 22:1300-07 et Revue Acomen 2000;6:69-77)

Appariements des ROIs



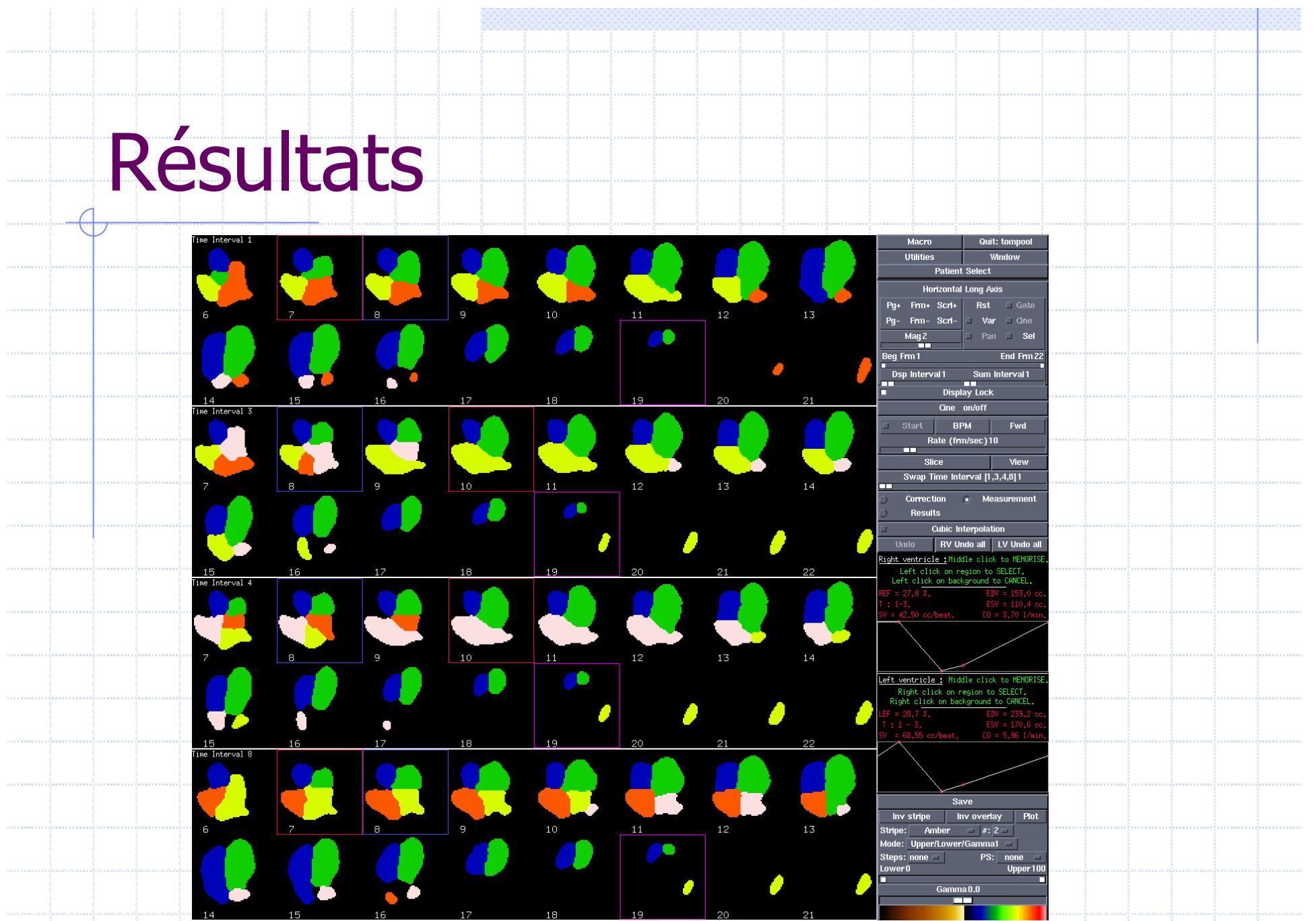
(Mariano-Goulart et al. EJNM 1998; 22:1300-07 et Revue Acomen 2000;6:69-77)

Appariements des ROIs



(Mariano-Goulart et al. EJNM 1998; 22:1300-07 et Revue Acomen 2000;6:69-77)

Résultats



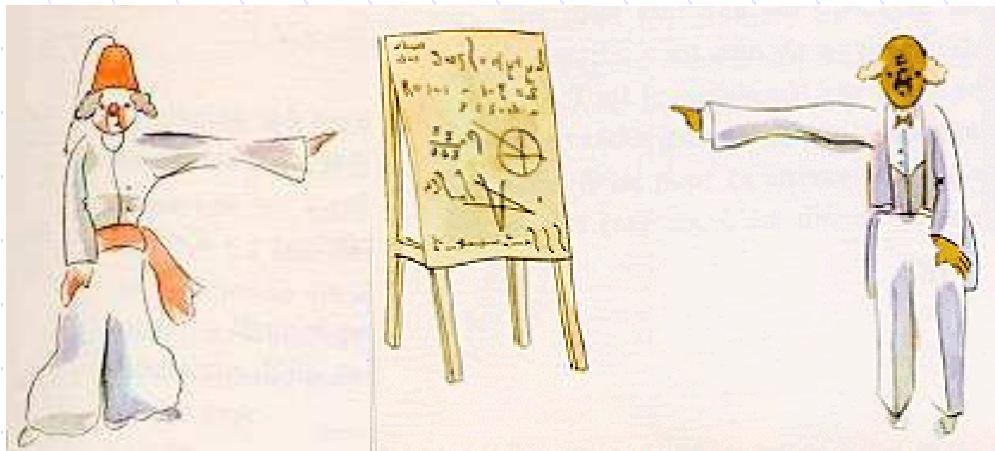
(Mariano-Goulart et al. EJNM 1998;22 et EJNM 2001;28- Daou et al. JNM 2001;42)

TROIS REFERENCES SIMPLES

[1] Desgrez A, Idy-Peretti I.
« Bases physiques de l'imagerie médicale »
Paris, Masson, 1991.

[2] M. Coster et J.L. Chermant.
« Précis d'analyse d'images »
Presses du CNRS, 1989.

[3] Schmitt M, Mattioli J.
« Morphologie mathématique »
Paris, Masson, 1993.



Merci de votre attention...

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