Spatiotemporal oriented filtering for dense motion field estimation in ultrasound imaging

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PhD Defense
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Outline

Outline

Ultrasound imaging

- Blood flow characterization $\Rightarrow$ fundamental clinical data
- Need for blood flow motion estimation methods
- Current methods suffers from some limitations

Objective of the thesis

Propose a new method to estimate blood flow motion that overcomes known limitations

General definitions

Ultrasound (US) imaging often used for blood flow evaluation

Advantages

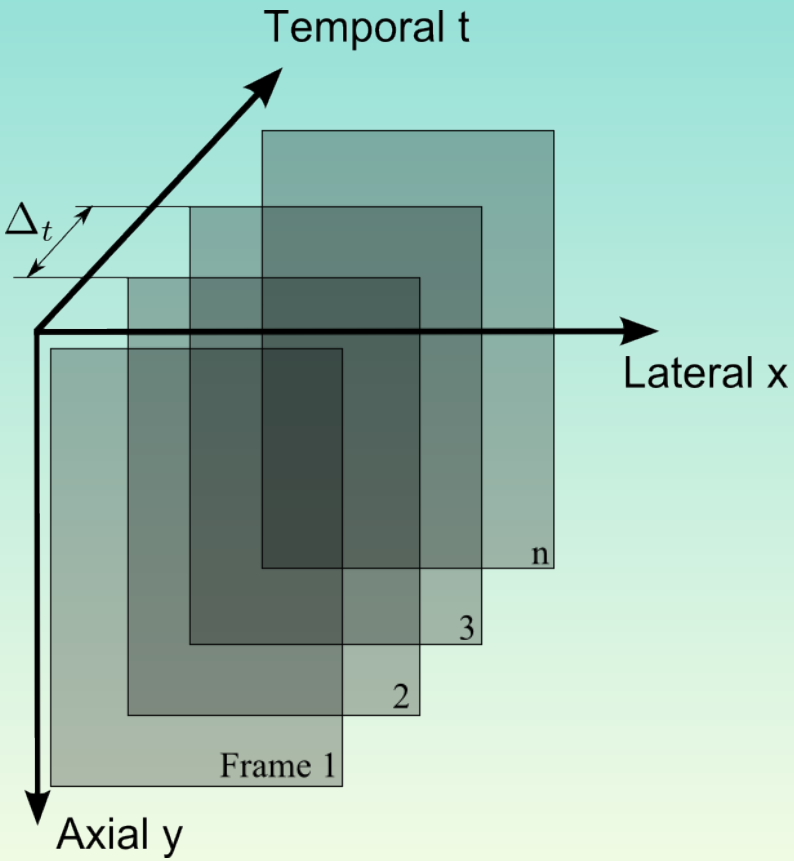
- low cost
- reduced size
  $\Rightarrow$ portable US systems
- non-invasive exam
- real time

Weaknesses

- limited resolution
- limited contrast
- operator-dependent

General definitions

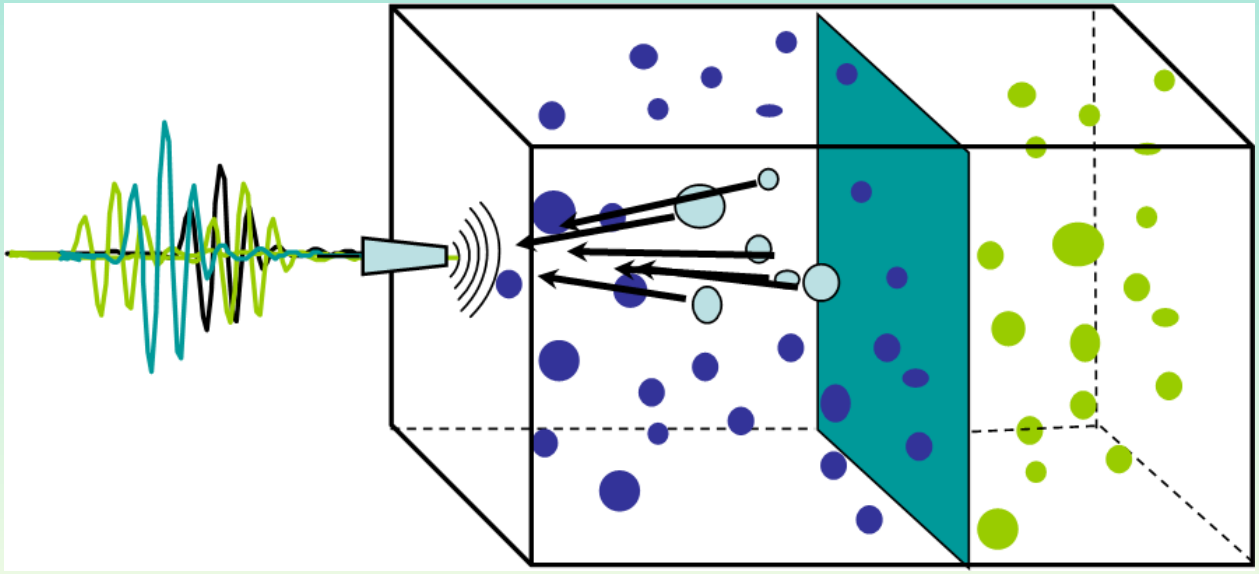
- Definition of the frame of reference



- x is the lateral direction
- y is the axial direction
- t is the temporal direction
- z is the azimuthal direction
- Δ_t is the time interval between two consecutive images

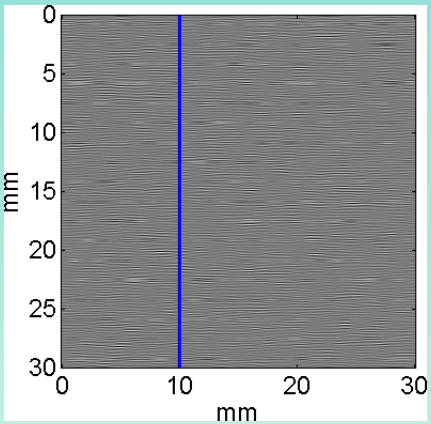
Formation of an ultrasonic signal

- Emission of an ultrasonic wave
- Backscattering of signal by scatterers in the medium
- Sum of several contributions to construct one signal



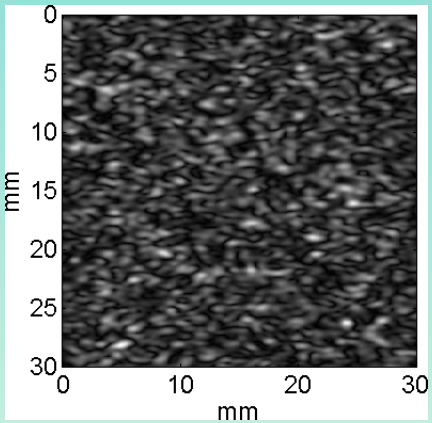
Different echographic signals

RF



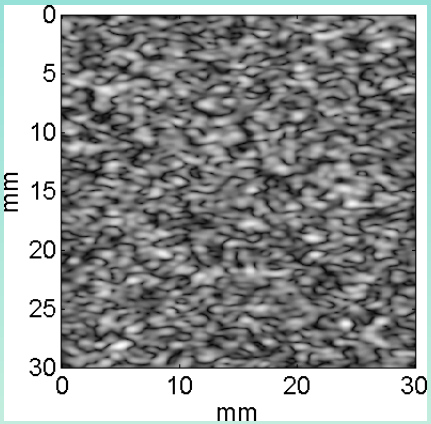
$\Longrightarrow$
Envelope detection

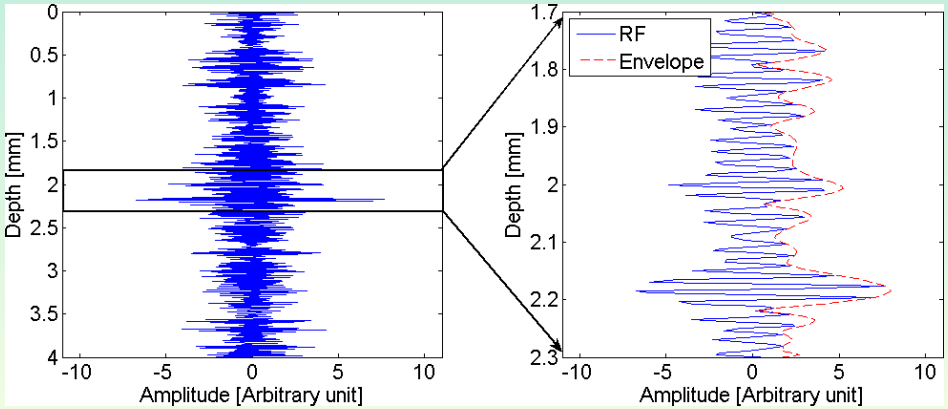
Envelope



$\Longrightarrow$
Logarithmic compression

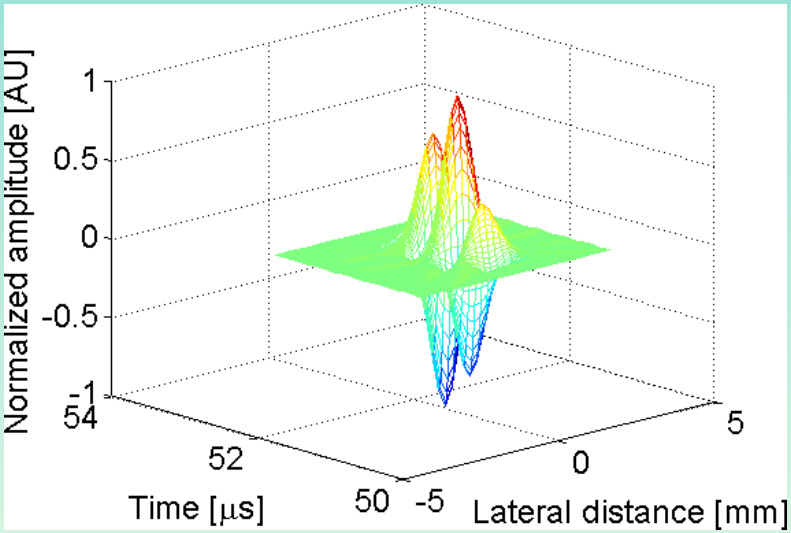
B-mode





Point Spread Function

- Point Spread Function (PSF) of a linear probe



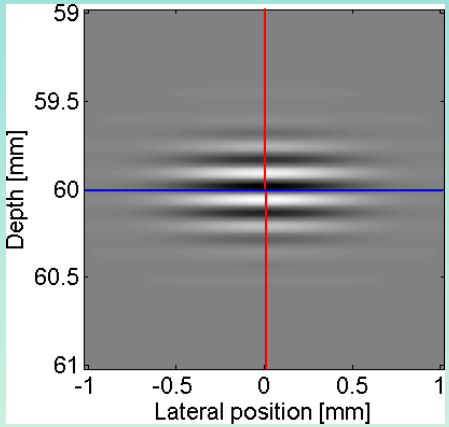
Simulated with Field II

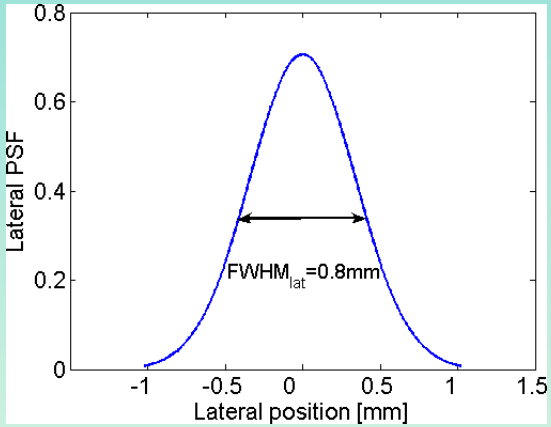
- Knowledge of PSF is important
- PSF is asymmetric
  $\Rightarrow$ narrower in the axial direction
- Gaussian shape

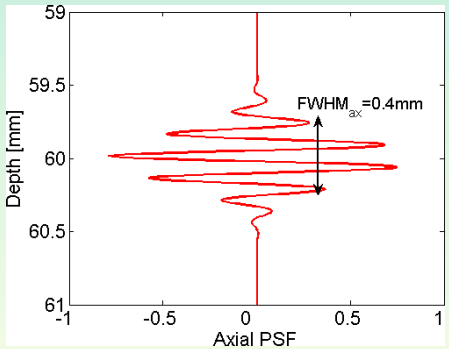
Resolution cell

Resolution cell

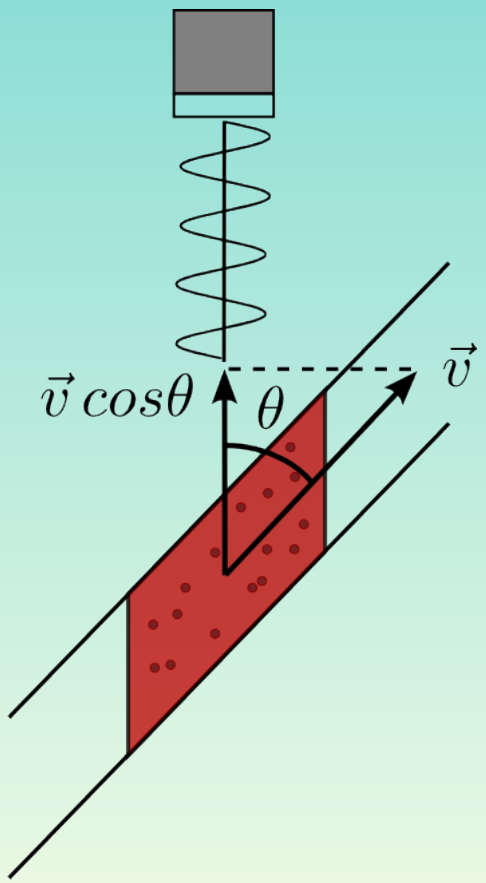
Full Width at Half Maximum (FWHM) of the PSF envelope







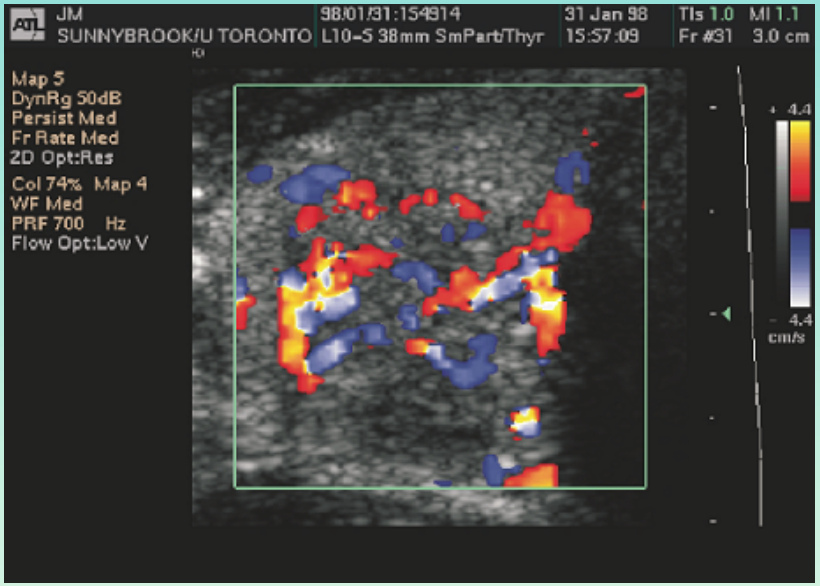
Doppler methods



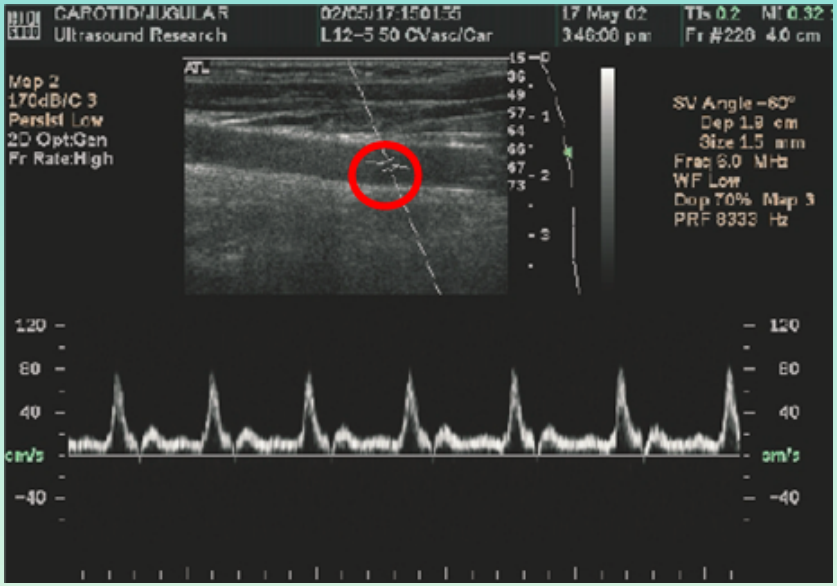
Doppler techniques are a reference

- Advantages
  - real time estimation
  - robust methods
- Weaknesses
  - Estimation of low velocities difficult
  - Limited spatial resolution
  - Axial component estimated

Illustrations of Doppler techniques



Color Doppler



Pulsed Doppler

Objectives

Motion estimation

Propose a method for blood flow velocities estimation from ultrasound image sequences

Data simulation

Propose a fast methodology adapted to simulation of large amount of flow sequences

Outline

Existing methods

Two families of methods for simulation of ultrasound images :

- Acoustical approach
  - use of acoustical propagation equations :
    Field II [Jensen, 96], DREAM [Piwakowsky & Sbai, 99]
  - Rayleigh's integral discrete representation :
    Ultrasim [Holm, 01]
- System approach
  - use of a linear convolution model :
    [Meunier & Bertrand, 95] [Gao et al., 09]

Existing methods

- Comparison of different approaches

	Advantages	Drawbacks
Field II	acoustical simulation	important simulation time, linear model
System approach	reduced simulation time	simplified model, constant PSF

Existing methods

- Comparison of different approaches

	Advantages	Drawbacks
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$\Longrightarrow$ **we chose system approach**

Linear convolution model

We define :

- $T(x, y, z)$ as the impulse response of explored medium
- $H(x, y, z)$ as the impulse response of imaging system

RF signal $S(x, y, z)$ is defined by [Meunier & Bertrand, 95] :

$$S(x, y, z) = H(x, y, z) \otimes T(x, y, z)$$

$$S(x, y, z) = \int\int\int T(\mu, \nu, \omega) \times H(x - \mu, y - \nu, z - \omega)\, d\mu d\nu d\omega$$

Linear convolution model

- Impulse response of system

$$H(x,y,z) = exp\left(-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2}+\frac{z^2}{\sigma_z^2}\right)\right).cos(2\pi fy)$$

- Impulse response of tissue

$$T(x,y,z) = \sum_n a_n \delta(x-x_n, y-y_n, z-z_n)$$

with a_n the amplitude of a scatterer located in (x_n, y_n, z_n)

Meunier's proposal

Question

Is it necessary to perform 3D convolution ?

Meunier & Bertrand propose an alternative to perform a 2D convolution instead of a 3D convolution assuming :

- constant azimuthal profil $H_z()$
- constant echogenicity at a given depth
- more than 5 scatterers per resolution cell

Meunier's proposal

Question

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Meunier & Bertrand propose an alternative to perform a 2D convolution instead of a 3D convolution assuming :

- constant azimuthal profil $H_z()$
- constant echogenicity at a given depth
- more than 5 scatterers per resolution cell

Limitation : scatterers remain within the imaging plane

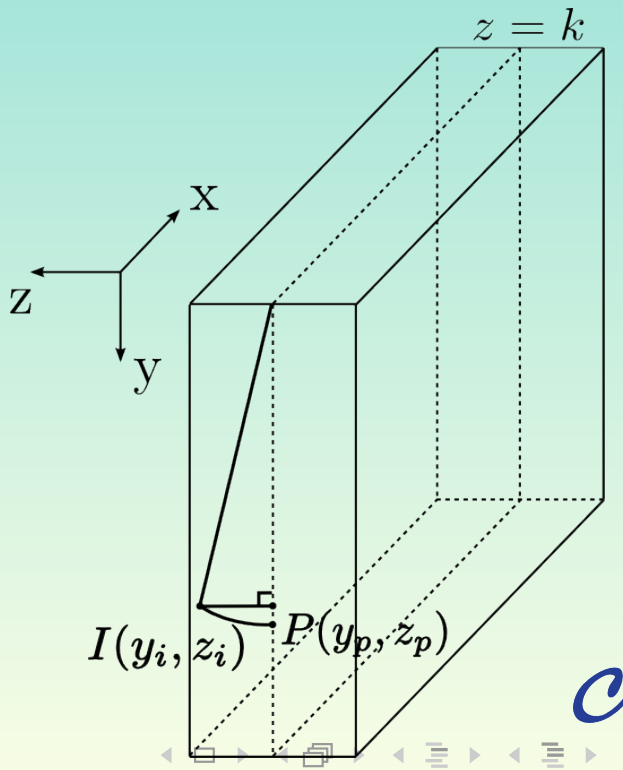
Our solution

Proposition

Account for 3D motion by projecting scatterers before 2D convolution [Marion & Vray, IEEE Trans. UFFC, 2009]

- Preservation of scatterers within $[k - 3\sigma_z, k + 3\sigma_z]$
- Projection I towards P

$$\begin{cases} x_p &= x_i \\ y_p &= \sqrt{y_i^2 + (z_i - k)^2} \\ z_p &= k \\ A_p &= A_i.exp\left(-\frac{(z_i - k)^2}{2\sigma_z^2}\right) \end{cases}$$



Convolution implementation

2 possible approaches for convolution :

- analytical expression
  for i = 1 to N_d,

$$\text{im} = \text{im} + A_i.exp\left[-0.5 * \left(\frac{x_i - x}{\sigma_x^2} + \frac{y_i - y}{\sigma_y^2}\right)\right] .cos\left(2\pi f\left(y_i - y\right)\right)$$

- numerical convolution with a grid
  - approximation of each scatterer to the closest node of a sampled grid
  - use of a numerical convolution algorithm

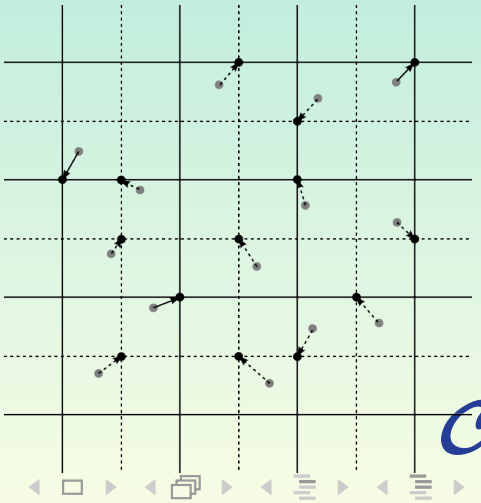
Convolution implementation

- Comparison of computation time for each approach

  Core 2 duo processor (2.66GHz) - 3Gb RAM

Size of Image	Size of PSF	Number of scatterers	CPU time [s] Direct	CPU time [s] Grid	Ratio
261*102	27*21	7700	84	0.014	6000
521*202	27*21	31600	1264	0.059	21400
1040*402	27*21	128000	15760	0.27	58300

- n the number of pixels
- complexity of direct method $O(n^2)$
- complexity of grid method $O(n)$



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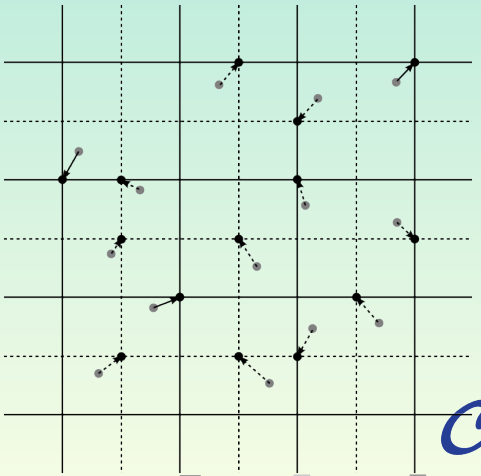
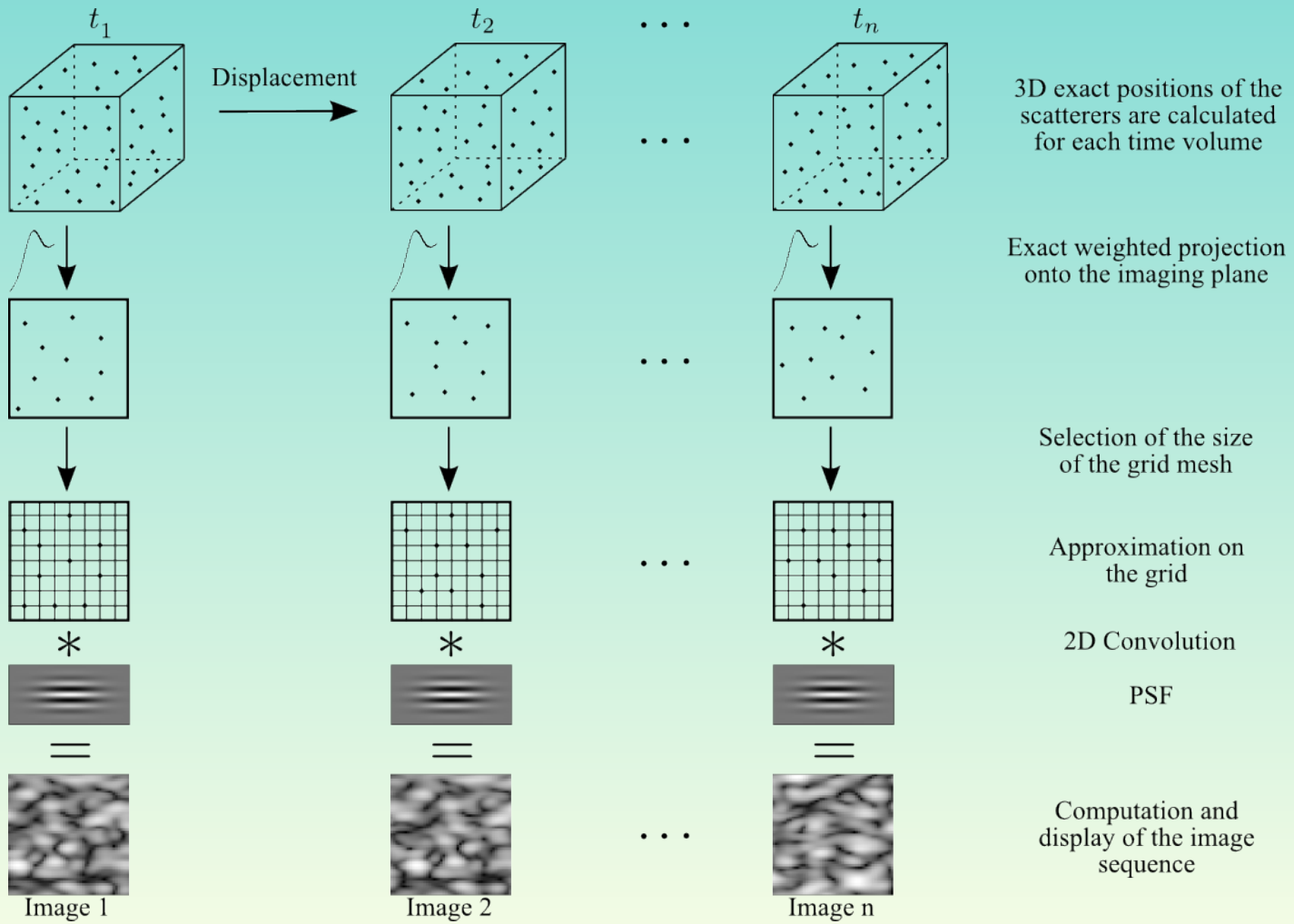
- n the number of pixels
- complexity of direct method $O(n^2)$
- complexity of grid method $O(n)$

$\Longrightarrow$ **We prefer the grid approach BUT mesh size is a critical parameter**

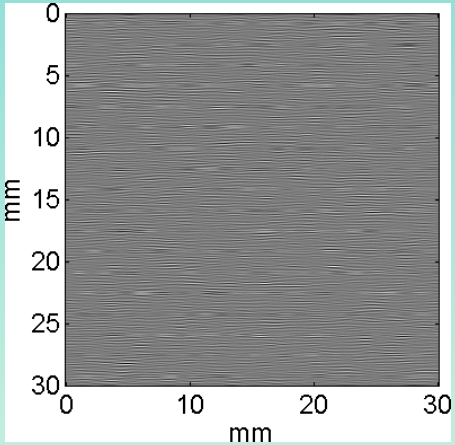


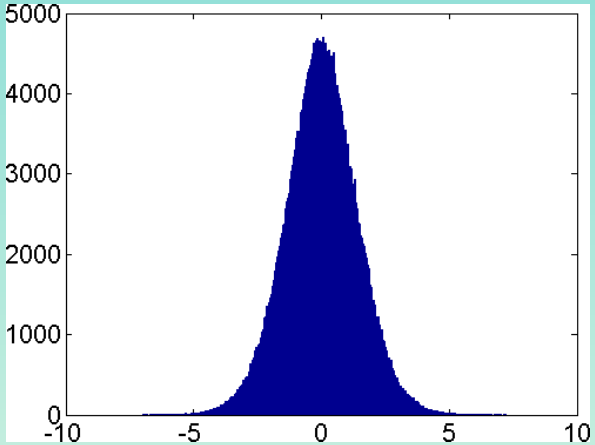
Synthesis scheme



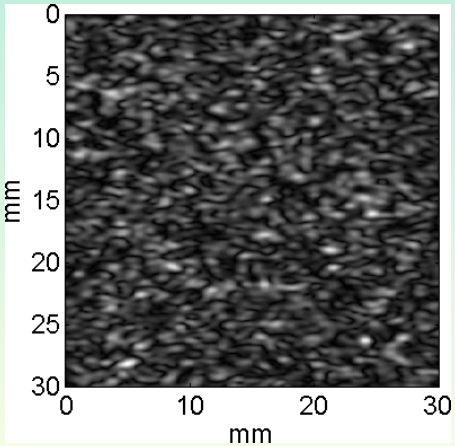
Statistics of simulated signals

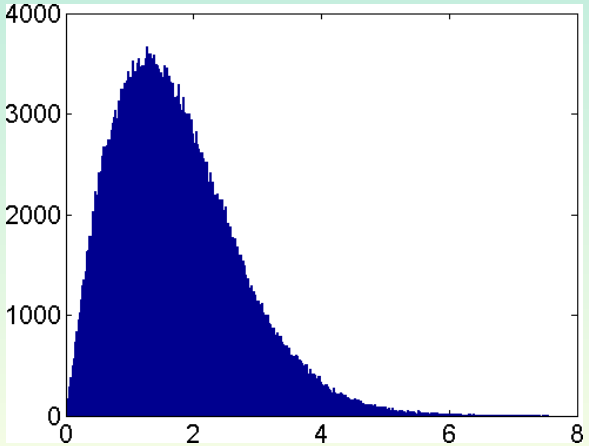
- First-order statistics of simulated data [Wagner et al., 83]





RF data
$\Rightarrow$ Gaussian distributed

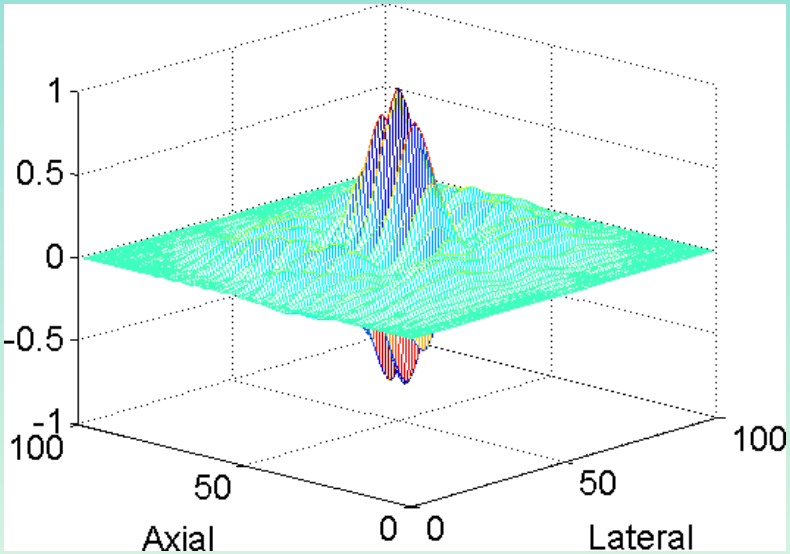




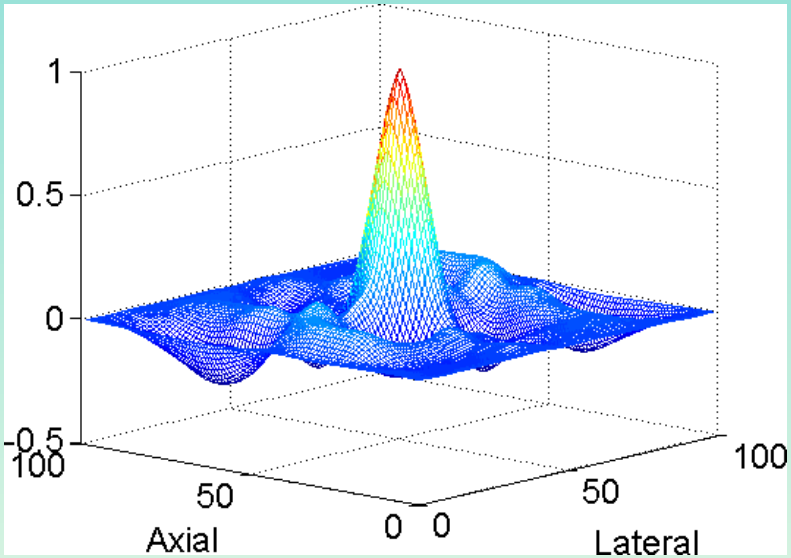
Envelope data
$\Rightarrow$ Rayleigh distributed

Statistics of simulated signals

- Second-order statistics of simulated data [Smith & Wagner, 84]



Autocovariance2D(RF)
≈
Autocovariance2D(PSF)



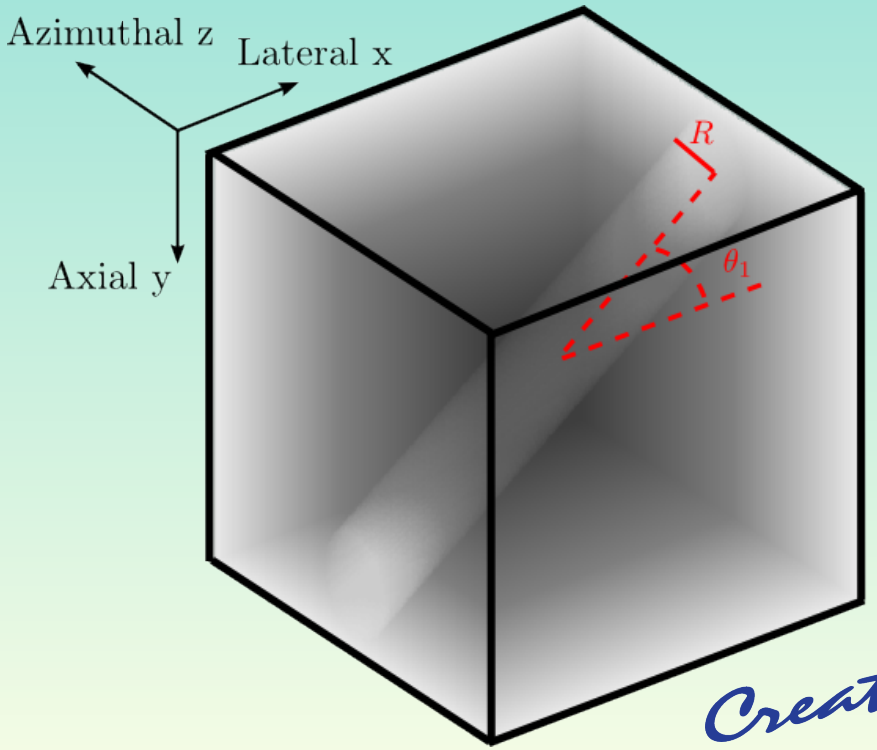
Autocovariance2D(env)
≈
PSF

Flow modelization

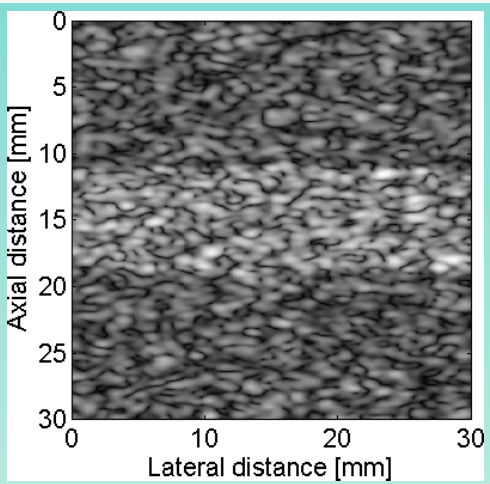
Objective

Modelization of blood flow motion

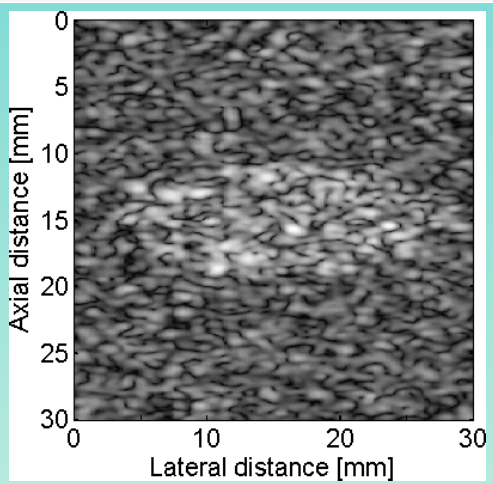
- θ_1 : vessel orientation within the imaging plane
  $\theta_1 = 30^\circ$
- θ_2 : out-of-plane vessel orientation
  $\theta_2 = 5^\circ$
- R : radius of the vessel
- V_{mean} : mean velocity



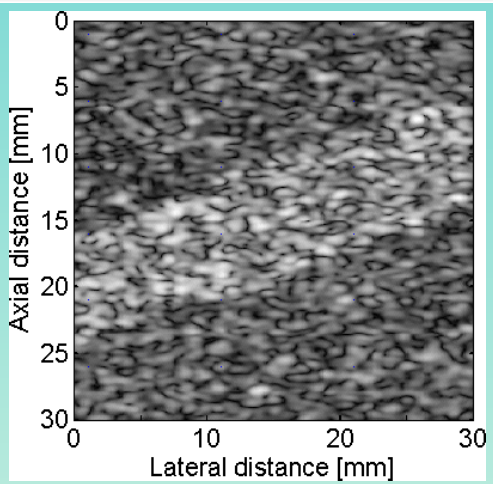
Validation of the displacement model



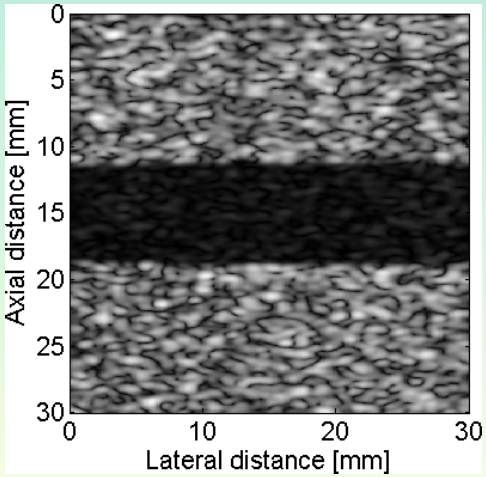
longitudinal

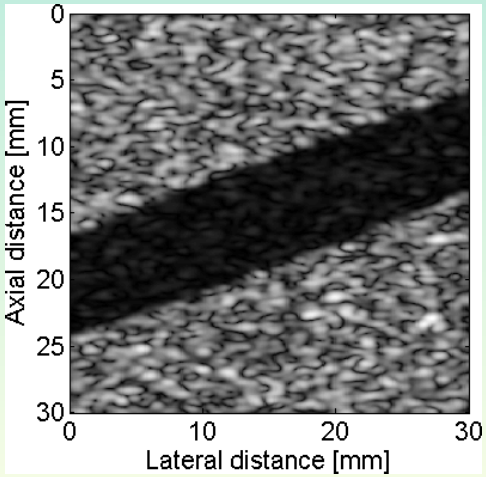


out-of-plane



oriented





Outline

Specific methods in US imaging

- Doppler-based methods
  - Time-shift estimation [Bonnefous & Pesqué, 86] [Hein & O'Brien, 93] [Viola & Walker, 03]
  - Phase-shift estimation **[Kasai et al., 85]** [Loupas et al., 95] [Jensen, 96]
  - Frequency-shift estimation [Ferrara & Algazi, 91] [Kouamé et al., 03]
- Multi-beam Doppler [Newhouse et al., 94] [Tortoli et al., 05]
- Synthetic aperture [Jensen & Munk, 98] [Anderson, 98] [Liebgott et al, 08]
- Decorrelation-based methods [Tuthill et al, 98] [Lupotti et al, 02] [Aoudi et al, 06]

Optical flow estimation methods

- Differential methods based on preservation of intensity
- Optical Flow Constraint Equation (OFCE)

$$\frac{\partial I}{\partial x} v_x + \frac{\partial I}{\partial y} v_y + \frac{\partial I}{\partial t} = 0$$

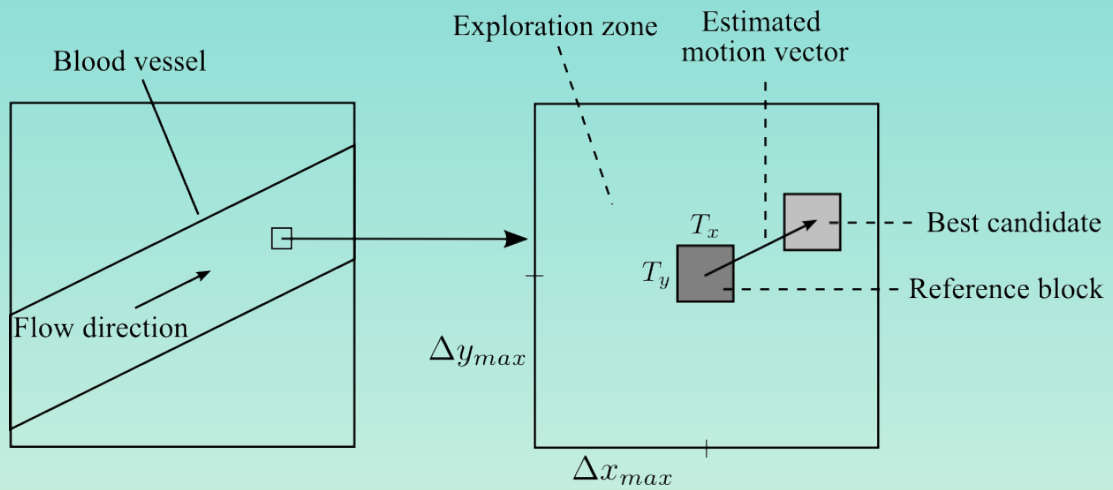
- 1 equation, 2 unknowns $\Rightarrow$ aperture problem
  - Spatial smoothing [Horn & Schunck, 81]
  - Locally constant optical flow [Lucas & Kanade, 81]
  - Directional smoothing [Nagel & Enkelmann, 86]

Difficulties

- No boundaries in US imaging
- Gradient operator
  - local $\Rightarrow$ high frequency in US data
  - global $\Rightarrow$ smoothing, reduce resolution
- Small displacements can be estimated

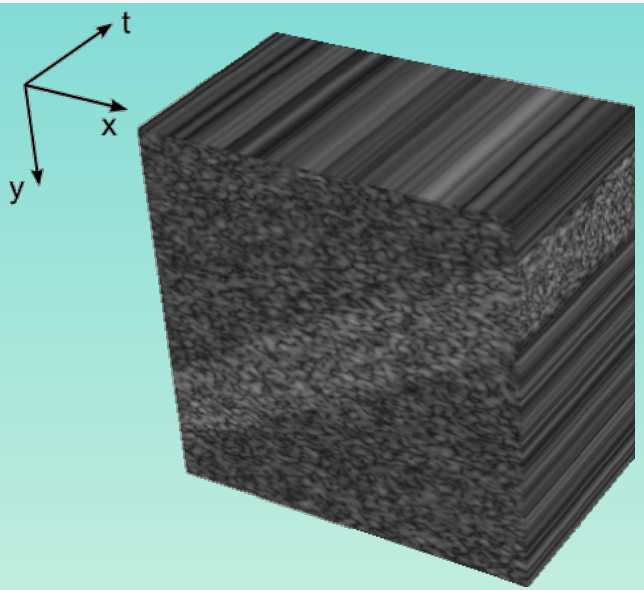
Block-matching methods

- Motion is visible



- 2 images : one reference block, several candidate blocks
- Hypothesis : constant motion within a block, constant value along time
- (dis)similarity criteria
- Rigid [Bohs et al., 00] or deformable [Basarab et al., 08]

Spatiotemporal/Spatiofrequential approaches

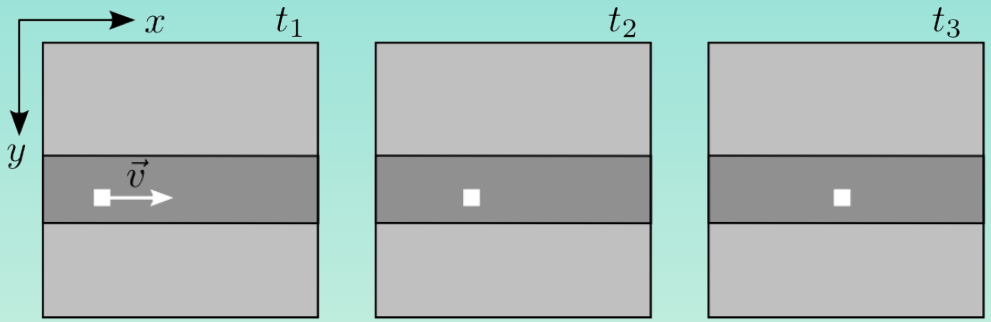


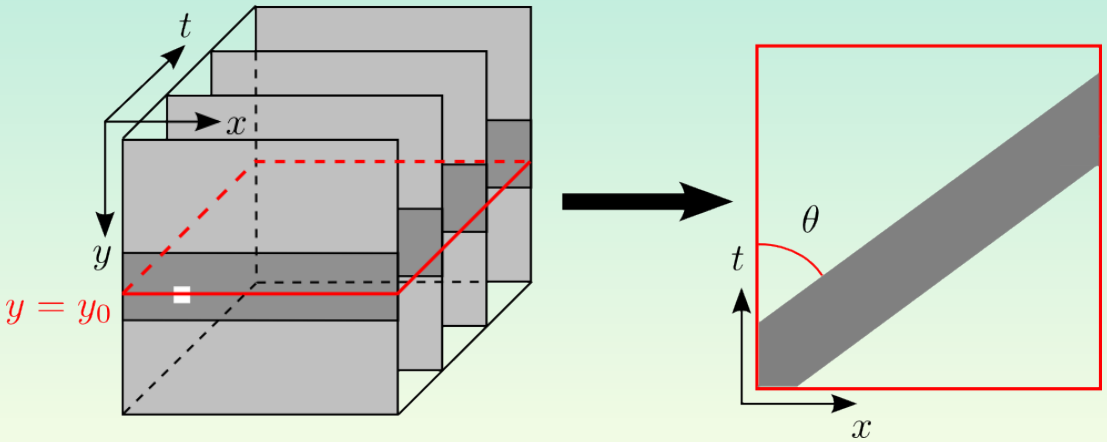
- Steerable filters [Adelson & Bergen, 85][Freeman and Adelson 87]
- Structure tensor [Bigün et al., 91] [Jähne, 93] [Lauze et al., 04]

- Physiological studies [Watson & Ahumada, 83] [Foster et al., 85] neuron $\Leftrightarrow$ spatiotemporal band-pass filters
- Spatiofrequential $\Rightarrow$ 3D Fourier spectrum $\approx$ plane [Jacobson & Wechsler, 87]
- Local estimation of the 2D plane [Simoncelli, 92] [Wilson & Gill, 93] [Oddershede et al., 08] [Marion & Vray, EUSIPCO, 2008]

2D Orientation in space-time data

- Moving object $\Rightarrow$ oriented pattern in space-time data

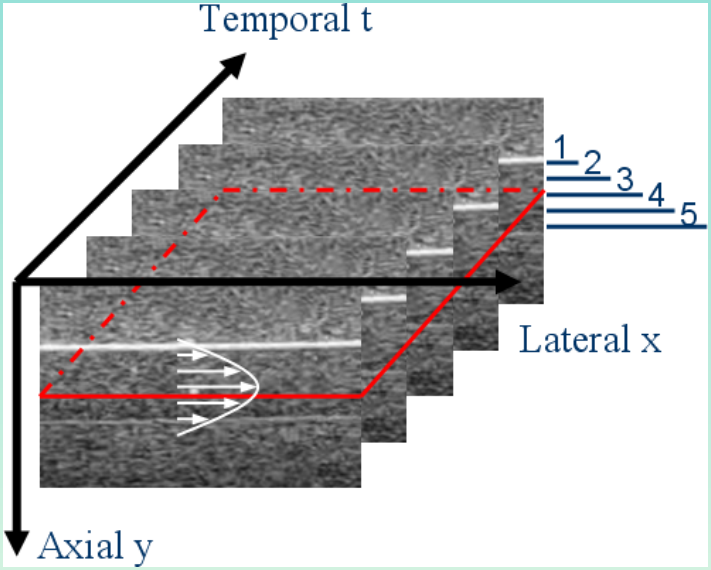




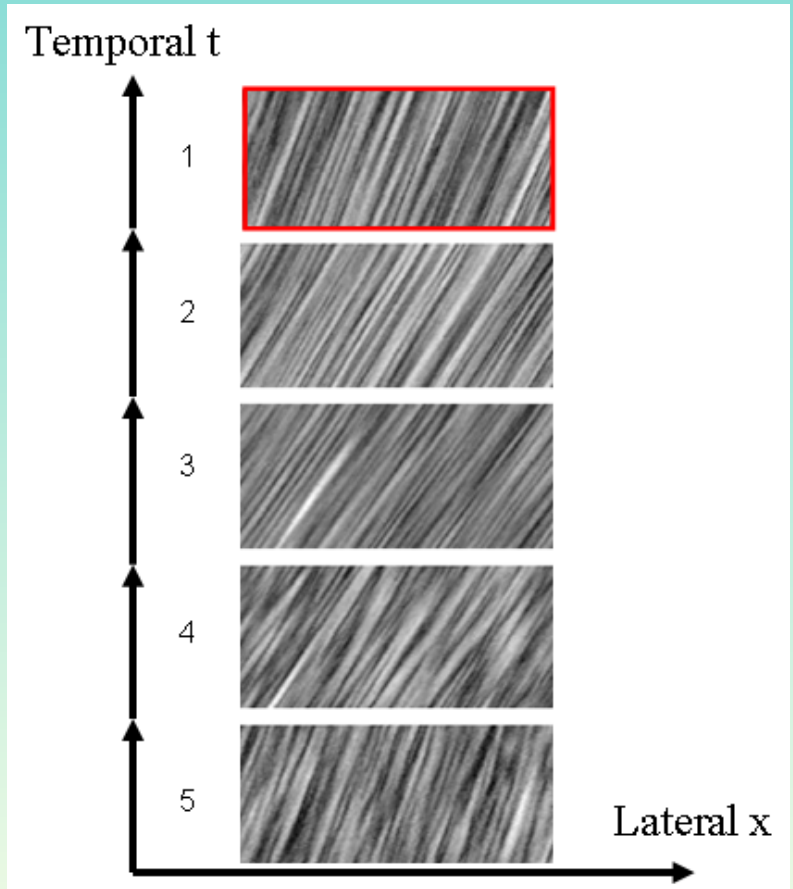
$$v = \frac{f_t}{f_s} tan\,(\theta)$$

f_t temporal sampling
f_s spatial sampling

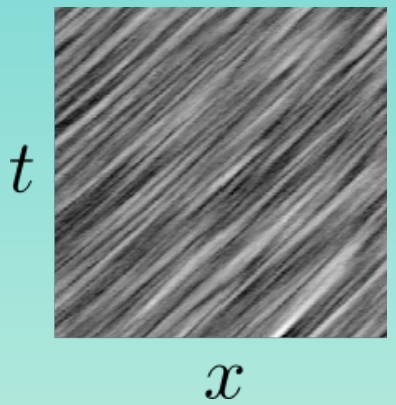
2D Orientation in space-time data

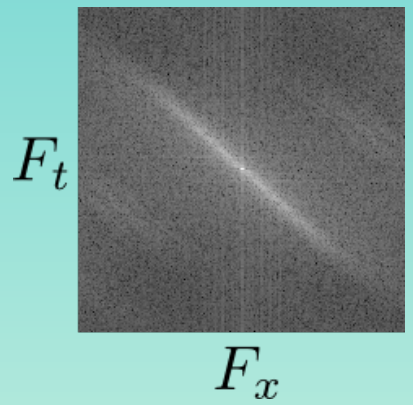


Proposition : estimate texture orientation with spatiotemporal oriented filtering



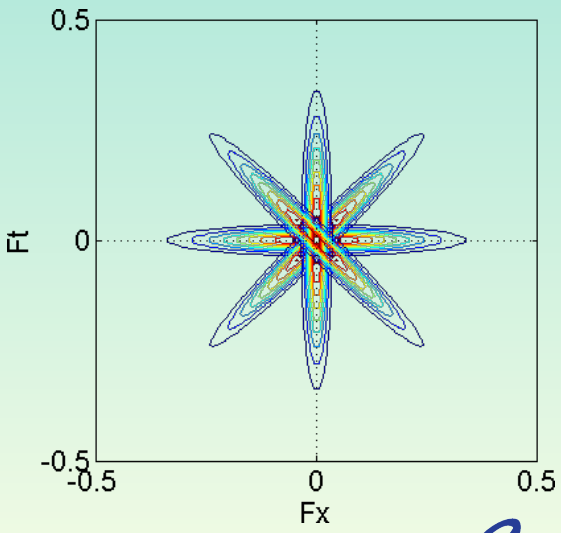
Fourier spectrum of US data





$$g(x,y) = \frac{1}{2\pi\sigma_x\sigma_y} exp\left(-\frac{x'^2}{2\sigma_x^2} - \frac{y'^2}{2\sigma_y^2}\right)$$

$$\begin{cases} x' = & x\cos\theta + y\sin\theta \\ y' = & -y\sin\theta + y\cos\theta \end{cases}$$



[Marion & Vray, GRETSI, 2007]

[Marion & Vray, IEEE Ultras. Symp., 2007]

Energy criterion

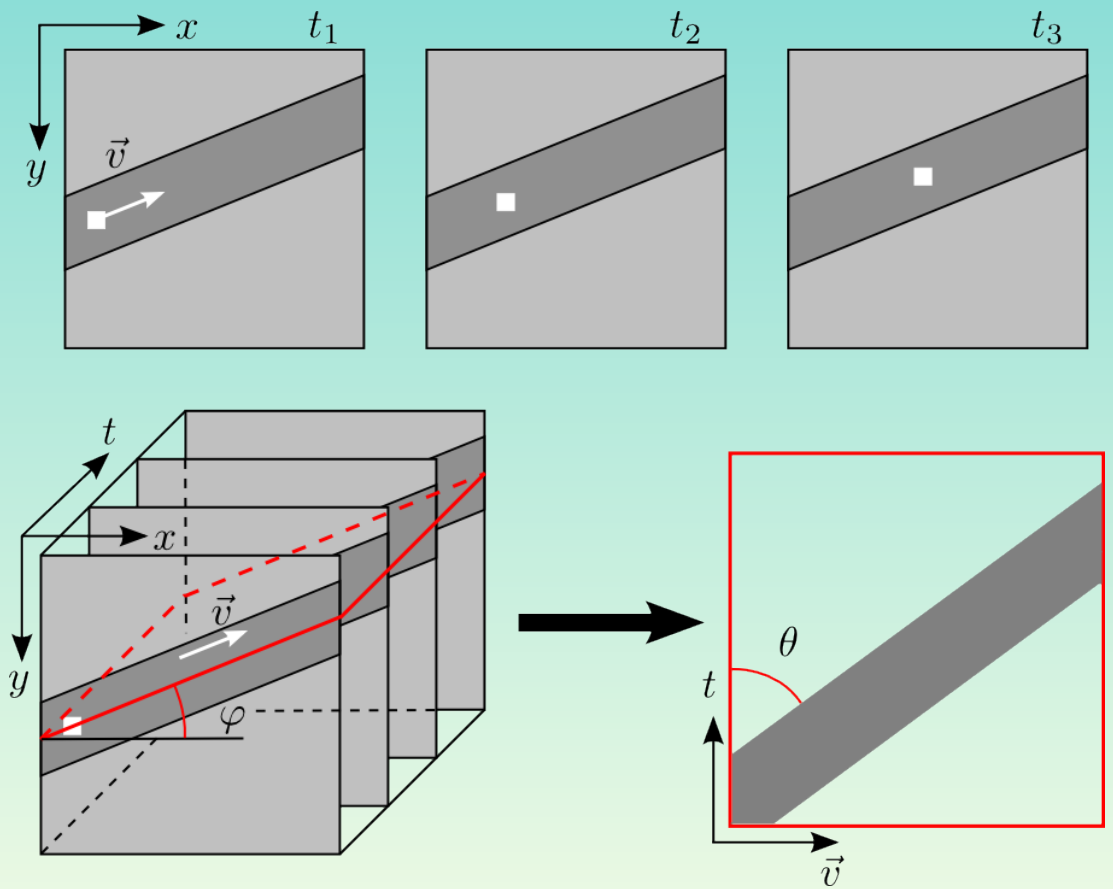
- I_θ : pixel values after filtering by θ-oriented filter
- Definition of an energy criterion

$$E(x,t,\theta) = \sum_{c=-C/2}^{C/2} \sum_{n=-N/2}^{N/2} \left(I_\theta(x+c,t+n) - \overline{I_\theta}(x,t) \right)^2$$

- Main orientation obtained by maximization of E

$$\widehat{\theta} = \underset{\theta}{\operatorname{argmax}}(E(x,t,\theta))$$

3D Orientation in space-time data

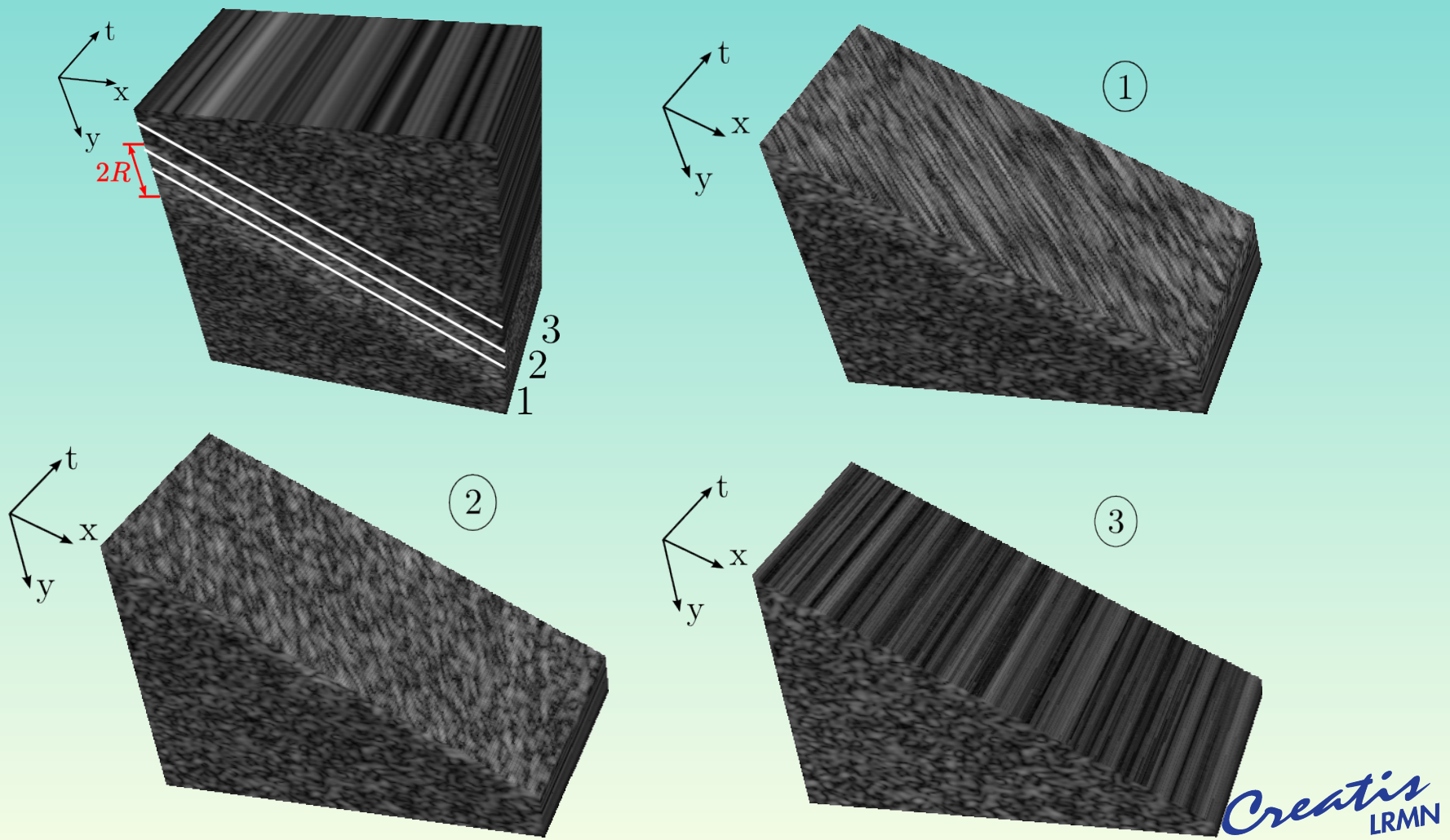


$$v_x = \frac{f_t}{f_x} \tan\theta . \cos\varphi$$

$$v_y = \frac{f_t}{f_y} \tan\theta . \sin\varphi$$

[Marion & Vray, Elsevier Pattern Recognition, 2009]

3D Orientation in space-time data



Construction of 3D spatiotemporal filters

- We define the filter by :

$$g(x,y,t) = \frac{1}{(2\pi)^{3/2}\sigma_x\sigma_y\sigma_t} exp\left(-\frac{x''2}{2\sigma_x^2} - \frac{y''^2}{2\sigma_y^2} - \frac{t''^2}{2\sigma_t^2}\right)$$

  where $(x''y''t'')$ are coordinates after rotations
- We have to bring the frame of reference $x''y''t''$ towards xyt
- Rotation $R_{-\theta,y}$ with an angle $-\theta$ around y-axis then rotation $R_{-\varphi,t'}$ with an angle $-\varphi$ around $t' = R_{-\theta,y}(t)$

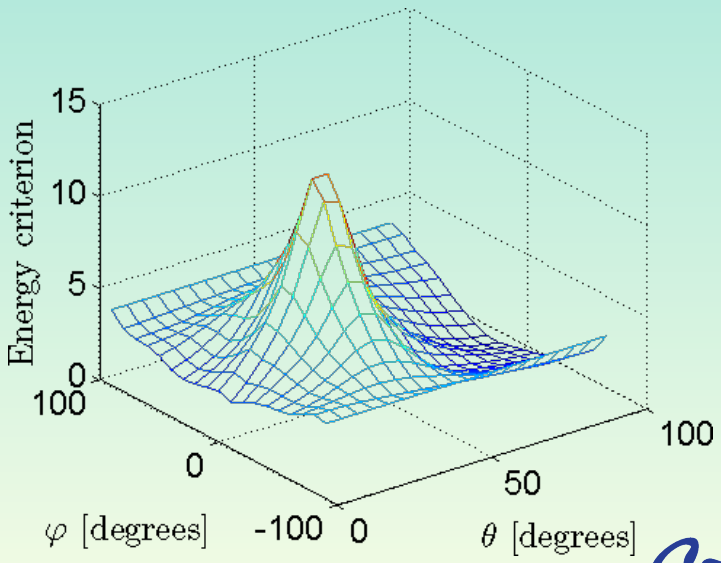
Energy criterion

- $I_{\varphi,\theta}$: pixel values after filtering by (φ, θ)-oriented filter
- Definition of an energy criterion

$$E(x, y, t, \varphi, \theta) = \sum_{c=-C/2}^{C/2} \sum_{l=-L/2}^{L/2} \sum_{n=-N/2}^{N/2} \left[I_{\varphi,\theta}(x + c, y + l, t + n) - \overline{I_{\varphi,\theta}}(x, y, t) \right]^2$$

- Main orientation obtained by maximization of E

$$\widehat{(\varphi, \theta)} = \underset{\varphi,\theta}{\operatorname{argmax}}(E(x, y, t, \varphi, \theta))$$



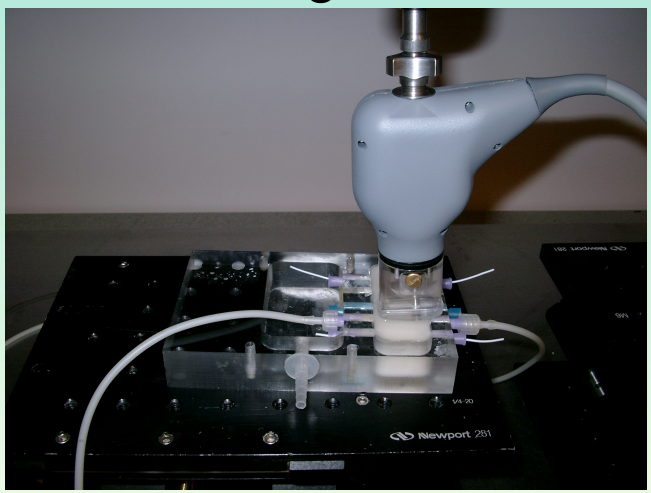
Sequences and performance criteria

- 9 experimental sequences (S_{fb1-5} and S_{fs6-9})
  - mean velocity from 0.25mm/s to 1.73mm/s
  - orientation from 0° to 8°
- 16 simulated sequences (S_{s1-16})
  - mean velocity from 0.4mm/s to 2mm/s
  - orientation from 0° to 30°

- Performance criteria
  - Estimated mean velocity components $\widehat{v_x}$
  - Estimated mean velocity components $\widehat{v_y}$
  - Estimated mean modulus $\widehat{|v|}$
  - Estimated mean orientation $\widehat{\varphi}$

Experimental configuration

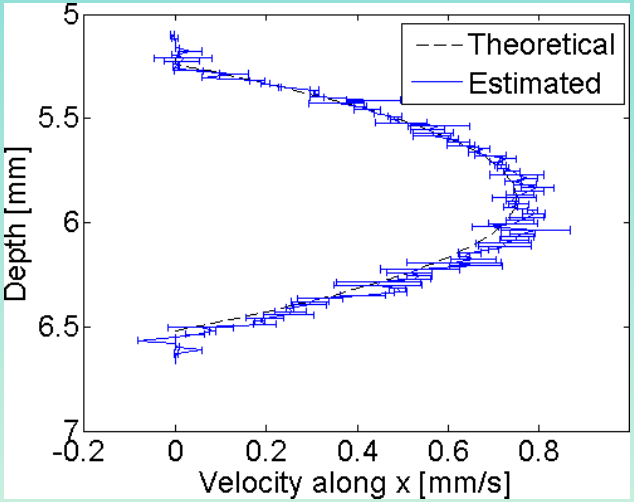
- Phantom
  - gelatin to simulate biological tissues
  - silica to replace scatterers
  - 1mm diameter vessel
- Blood mimicking fluid



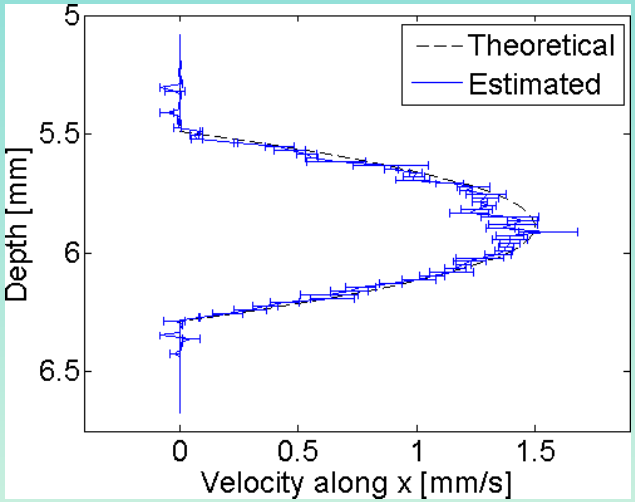
- Imaging system
  - Vevo 660, VisualSonics, Toronto (40MHz)
  - B-mode image sequences
  - Axial resolution : 40μm
  - Lateral resolution : 80μm

Results with 2D oriented filtering

- Purely lateral motion



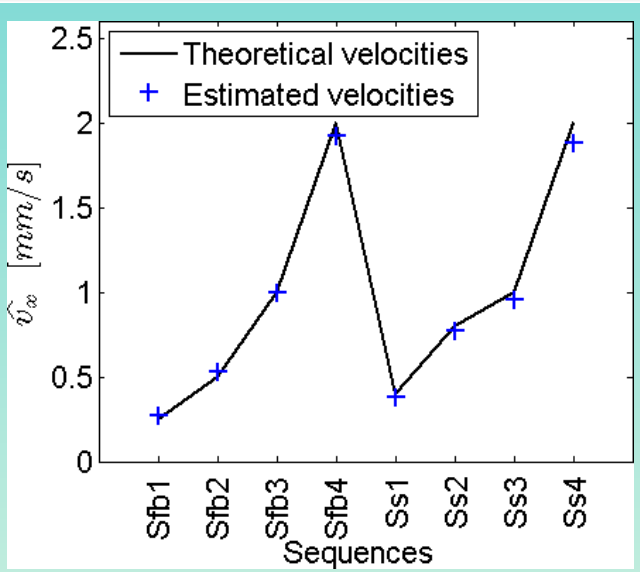
S_{fb2} (experimental)



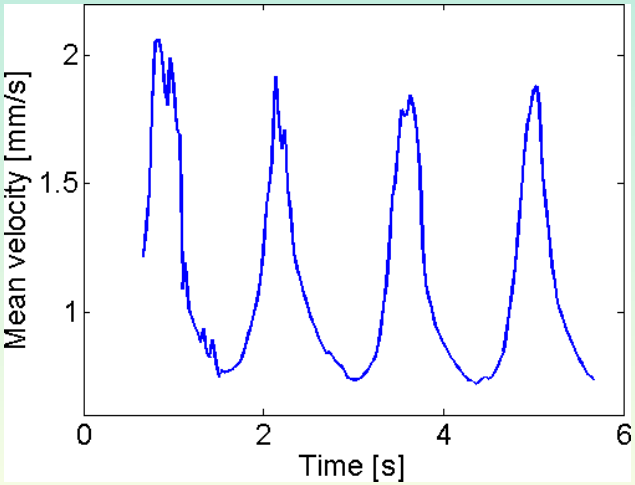
S_{s3} (simulated)

- Normalized mean values and standard deviations calculated along 15 temporal frames
- Velocity profile is well estimated
- Low standard deviations

Results with 2D oriented filtering



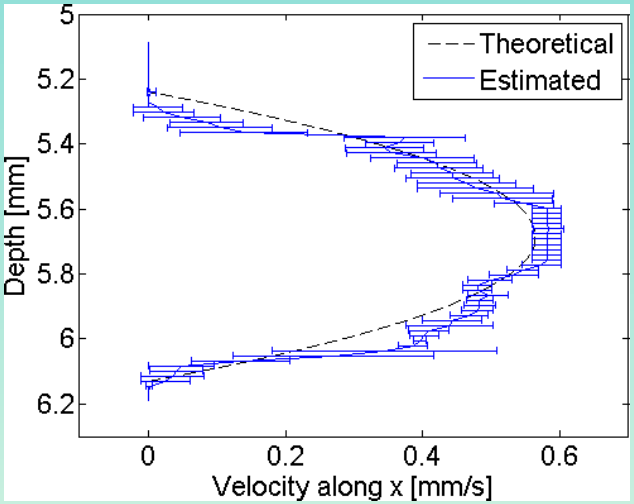
- Estimated mean velocities for each sequence
- Close to theoretical values



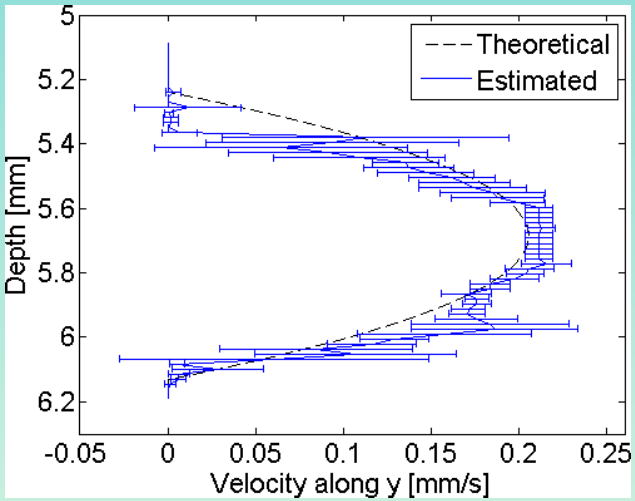
- Pulsed flow
- Estimated mean velocities $\approx$ 1.05mm/s

Results with 3D oriented filtering

- 2D motion estimated from S_{s9} (simulated, 20°)



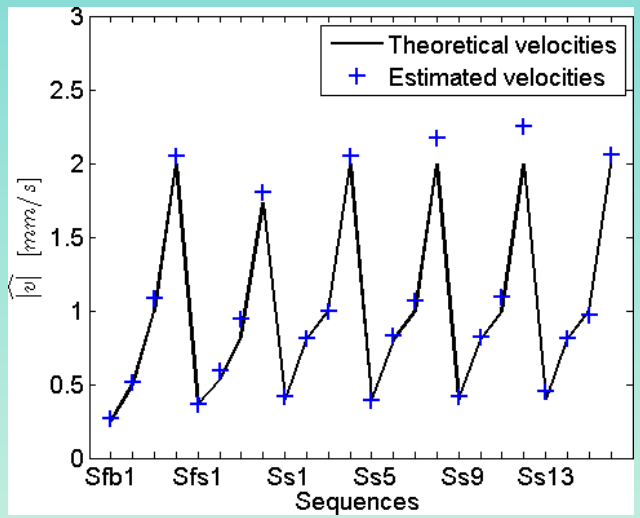
V_x profile



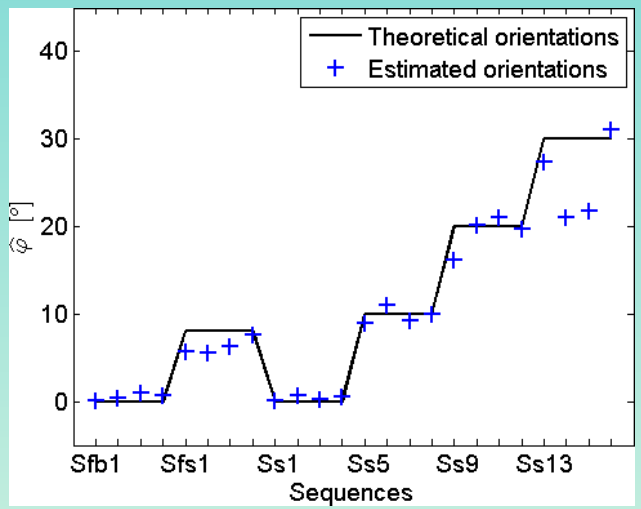
V_y profile

- Estimates globally less precise than with 2D filtering
- Errors between theoretical and estimated profiles are increased
- Standard deviations are also increased

Results with 3D oriented filtering



$\widehat{|v|}$

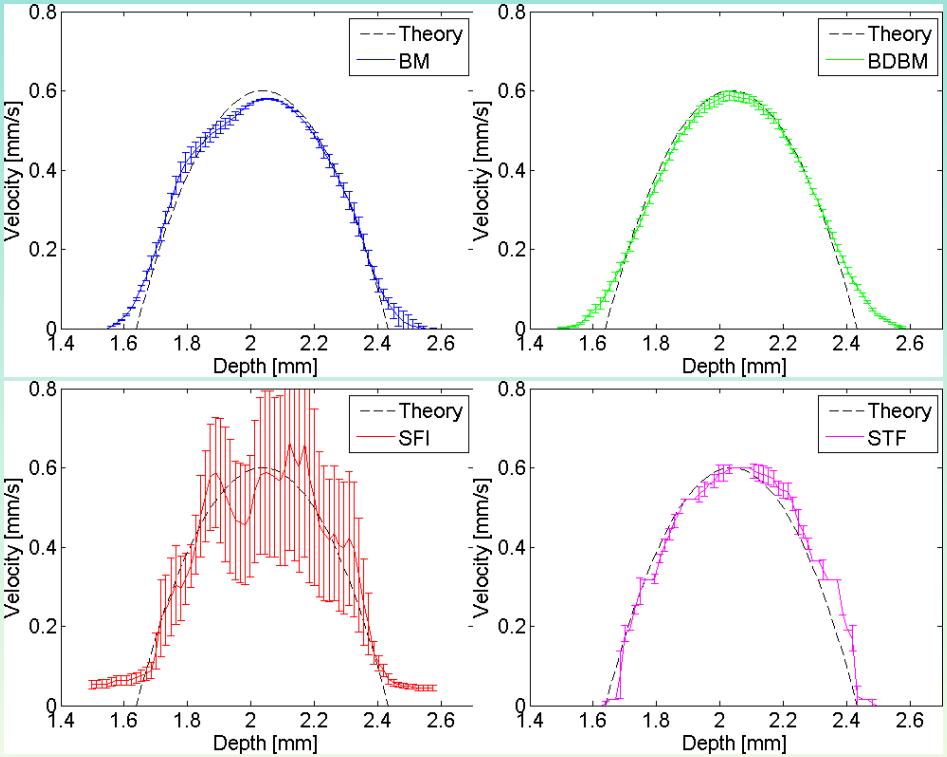


$\widehat{\varphi}$

- Loss of precision when velocity increases
- Orientations are more difficult to estimate
- Errrors on velocity components due to orientation rather than modulus

Comparison with other methods

- 3 motion estimation methods, S_{s1} (simulated, 0°)



- Speckle Flow Index
  $\Rightarrow$ CPU Time Ratio $= 1$
- **Spatiotemporal Filtering**
  $\Rightarrow$ CPU Time Ratio ≈ 2500
- Block Matching
  $\Rightarrow$ CPU Time Ratio ≈ 6000
- Bilinear Deformable Block Matching
  $\Rightarrow$ CPU Time Ratio ≈ 6000

Outline

Contributions

- Simulation of ultrasound data
  - Efficient methodology for fast simulation of ultrasound image sequences
  - Simulated database for evaluation of blood flow estimation algorithms
- Blood flow motion estimation
  - New method based on a spatiotemporal approach
  - Evaluation with a large set of sequences
  - Encouraging results for difficult situations

Perspectives

- Use of RF signals to study small displacements
  - more precise estimates but smaller range of velocities
- Investigate other spatiotemporal approaches
  - Preliminary results with structure tensor method
- Improvement of the simulator
  - Reduce simulation time for a real-time application
    [Marion et al., IEEE Ultras. Symp., 2009]
- Evaluation with more conventional data (5MHz)
  - Ultrasonix

Personal bibliography

International journals

A. Marion and D. Vray

Spatiotemporal filtering of sequence of ultrasound images to estimate a dense field of velocities.
in Elsevier Pattern Recognition, Vol. 42, No. 11, pp. 2989-2997, 2009.

A. Marion and D. Vray

Toward a real-time simulation of ultrasound image sequences based on a 3D set of moving scatterers.
in IEEE Transactions on Ultrasonics, Ferroelectrics and Frequency Control, in-press, 2009.

National conferences with proceedings

A. Marion and D. Vray

Filtrage spatiotemporel de séquences d'images ultrasonores pour l'estimation d'un champ dense de vitesses.
in Actes du colloque GRETSI, Troyes, France, pp. 73-76, 2007.

A. Marion and D. Vray

Estimation de vitesses à partir de séquences d'images ultrasonores.
in Actes de MAJECSTIC, Marseille, France, CD, 2008.

Personal bibliography

International conferences with proceedings

A. Marion and D. Vray

Blood velocity estimation based on 3D spatiotemporal filtering of sequences of ultrasound images.
in Proceedings of IEEE Ultrasonics Symposium, New-York, NY, USA, pp. 2461-2464, 2007.

A. Marion and D. Vray

Velocity estimation with 3D spatiotemporal filtering of sequences of ultrasound images : a Fourier approach.
in Proceedings of European Signal Processing Conference (EUSIPCO), Lausanne, Switzerland, EURASIP web, 2008.

A. Marion, W. Aoudi, A. Basarab, P. Delachartre and D. Vray

A comparative study of four vector velocity estimation methods applied to flow imaging.
in Proceedings of International Congress on Ultrasonics (ICU), Santiago, Chile, in-press, 2009.

Y. Liu, A. Marion and D. Vray

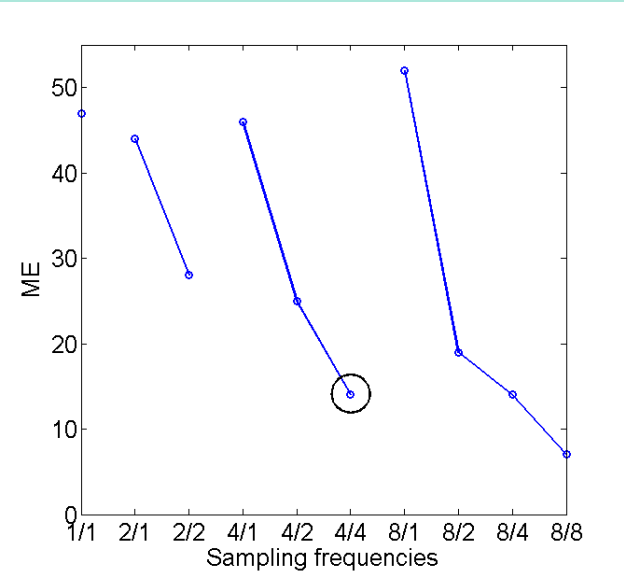
2D velocity estimation based on Wigner-Ville distribution with swept-scan imaging system.
in Proceedings of International Congress on Ultrasonics (ICU), Santiago, Chile, in-press, 2009.

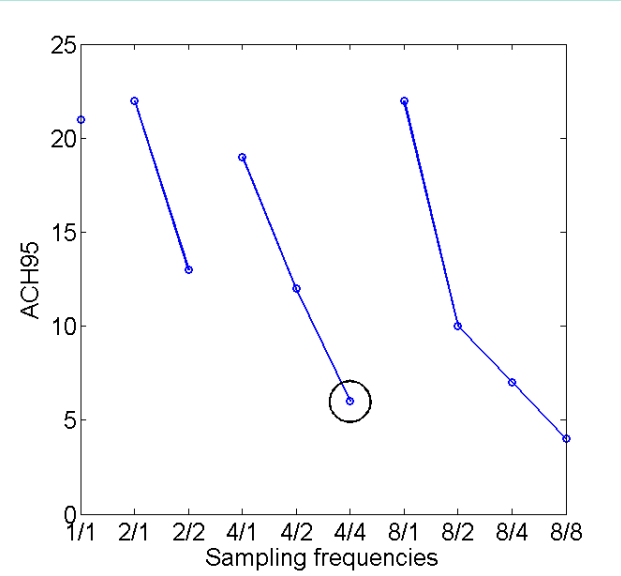
A. Marion, J. Porée and D. Vray

CREASIMUS : a fast simulator of ultrasound image sequences using 3D tissue motion.
in Proceedings of IEEE Ultrasonics Symposium, Roma, Italy, to appear, 2009.

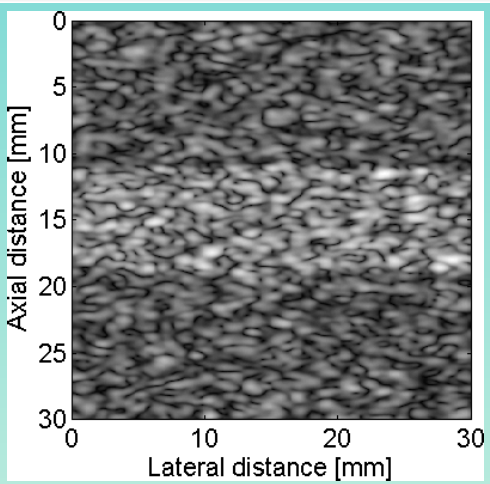
Grid approximation errors

- ME : maximum error
- ACH95 : abscissa of cumulative histogram superior to 95%
- Evolution as a function of oversampling coefficients

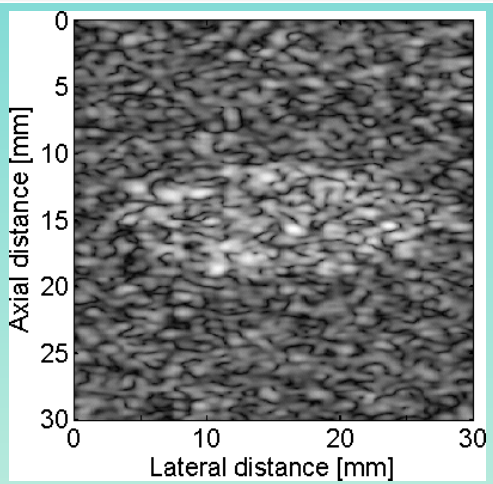




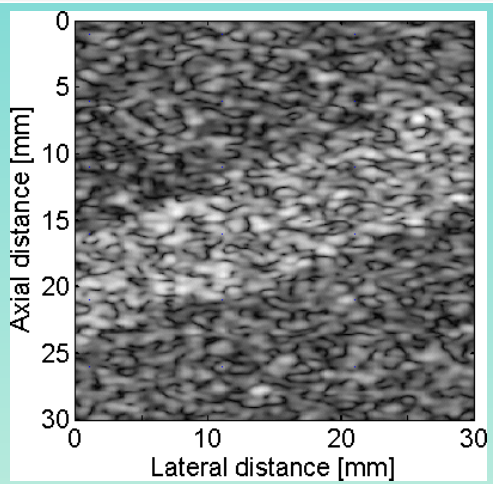
Validation of the displacement model



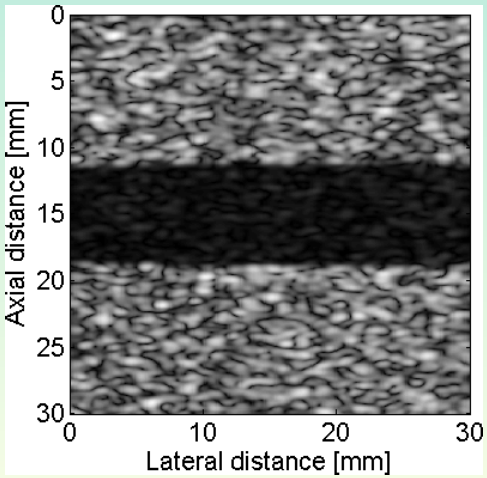
longitudinal

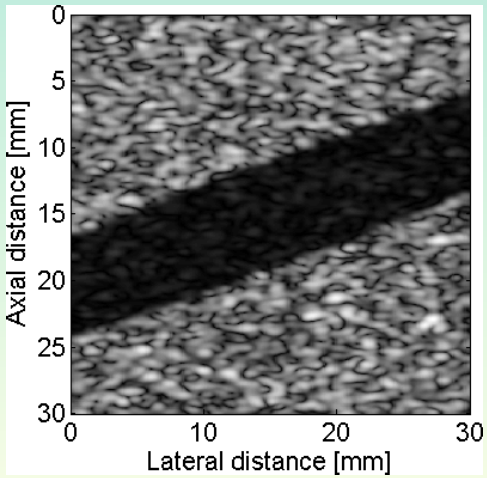


out-of-plane



oriented



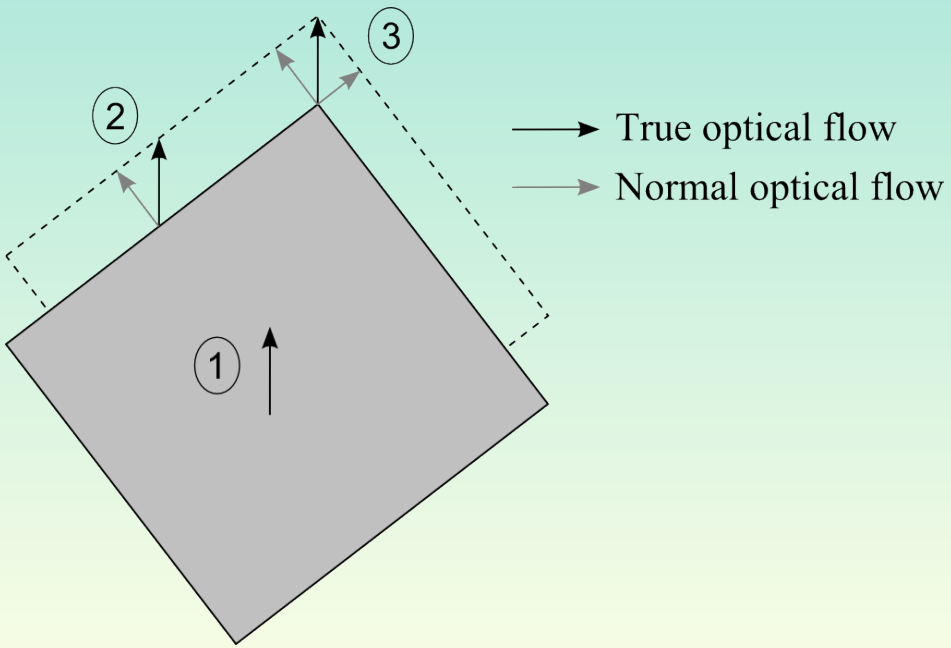


Optical flow estimation methods

- Differential methods based on preservation of luminosity
- Optical Flow Constraint Equation (OFCE)

$$\frac{\partial I}{\partial x} v_x + \frac{\partial I}{\partial y} v_y + \frac{\partial I}{\partial t} = 0$$

- 1 equation, 2 unknowns $\Rightarrow$ aperture problem



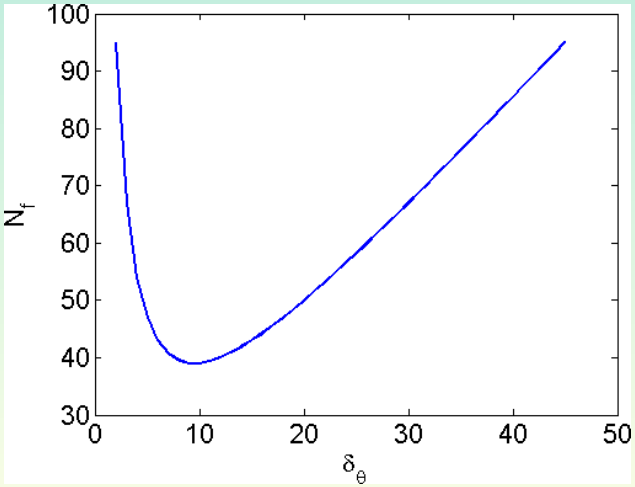
1. Null gradient
   $\Rightarrow$ NO
2. Unidirectional gradient
   $\Rightarrow$ NO
3. Bidirectional gradient
   $\Rightarrow$ OK

Optimization of research strategy

- For steady flow $\Rightarrow$ 2 steps filtering
- Coarse estimation θ_1 with angular resolution δ_θ
- Fine estimation θ_2 with angular resolution 1°

$$N_f(\delta_\theta) = 180/\delta_\theta + 2 * \delta_\theta + 1$$

with N_f the number of filters



- Minimization of δ_θ gives us $\delta_\theta = 9$ or $\delta_\theta = 10$
  $\Rightarrow 180/39 \approx 4.6$

Quaternion algebra : some definitions

- $R_{2\psi,\vec{V}_n}$ a rotation around $\vec{V}_n$ with angle 2ψ
- Q the associated quaternion :

$$\begin{aligned} Q &= a + b.i + c.j + d.k \\ Q &= (cos\psi, sin\psi\vec{N}) \end{aligned}$$

- $\vec{U}'$ rotated vector of $\vec{U}$ by rotation R is given by :

$$(0, \vec{U}') = \left(0, R_{2\psi,\vec{V}_n}(\vec{U})\right) = (cos\psi, sin\psi\vec{V}_n).(0, \vec{U}).(cos\psi, -sin\psi\vec{V}_n)$$

Construction of 3D spatiotemporal filters

- We define Q_1 associated to $R_{-\theta,y}$

$$Q_1 = cos\left(\frac{-\theta}{2}\right) + sin\left(\frac{-\theta}{2}\right) j$$

- We compute t' from :

$$(0,\vec{t'}) = \left(cos\left(\frac{-\theta}{2}\right) + sin\left(\frac{-\theta}{2}\right) j\right).(0,\vec{t}).\left(cos\left(\frac{-\theta}{2}\right) - sin\left(\frac{-\theta}{2}\right) j\right)$$

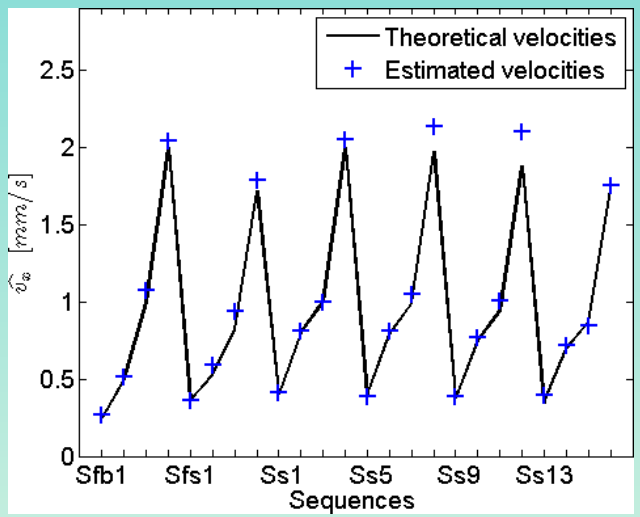
- We then define Q_2 associated to $R_{-\varphi,t'}$

$$Q_2 = cos\left(\frac{-\varphi}{2}\right) + sin\left(\frac{-\varphi}{2}\right)\vec{t'}(1) + sin\left(\frac{-\varphi}{2}\right)\vec{t'}(2) + sin\left(\frac{-\varphi}{2}\right)\vec{t'}(3)$$

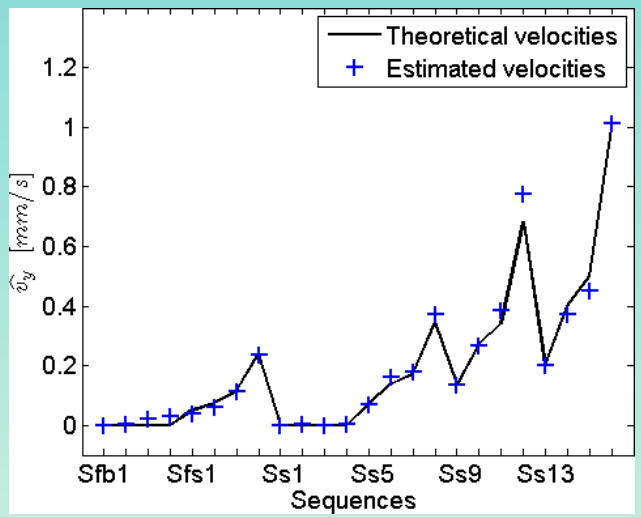
Performance criteria

- Local criteria
  - Normalized mean error $\overline{E_x}$
  - Normalized mean error $\overline{E_y}$
  - Normalized mean standard deviations $\overline{std_x}$
  - Normalized mean standard deviations $\overline{std_y}$
- Global criteria
  - Estimated mean velocity components $\widehat{v_x}$
  - Estimated mean velocity components $\widehat{v_y}$
  - Estimated mean modulus $\widehat{|v|}$
  - Modulus mean standard deviation $std_{|v|}$
  - Estimated mean orientation $\widehat{\varphi}$
  - Orientation mean standard deviation std_{φ}

Results with 3D oriented filtering



$\widehat{v_x}$



$\widehat{v_y}$

- Global criteria to evaluate reliability of estimates
- Velocity components are globally well estimated
- Saturation phenomenon