

– Ultrasound motion imaging –

Speckle tracking



by
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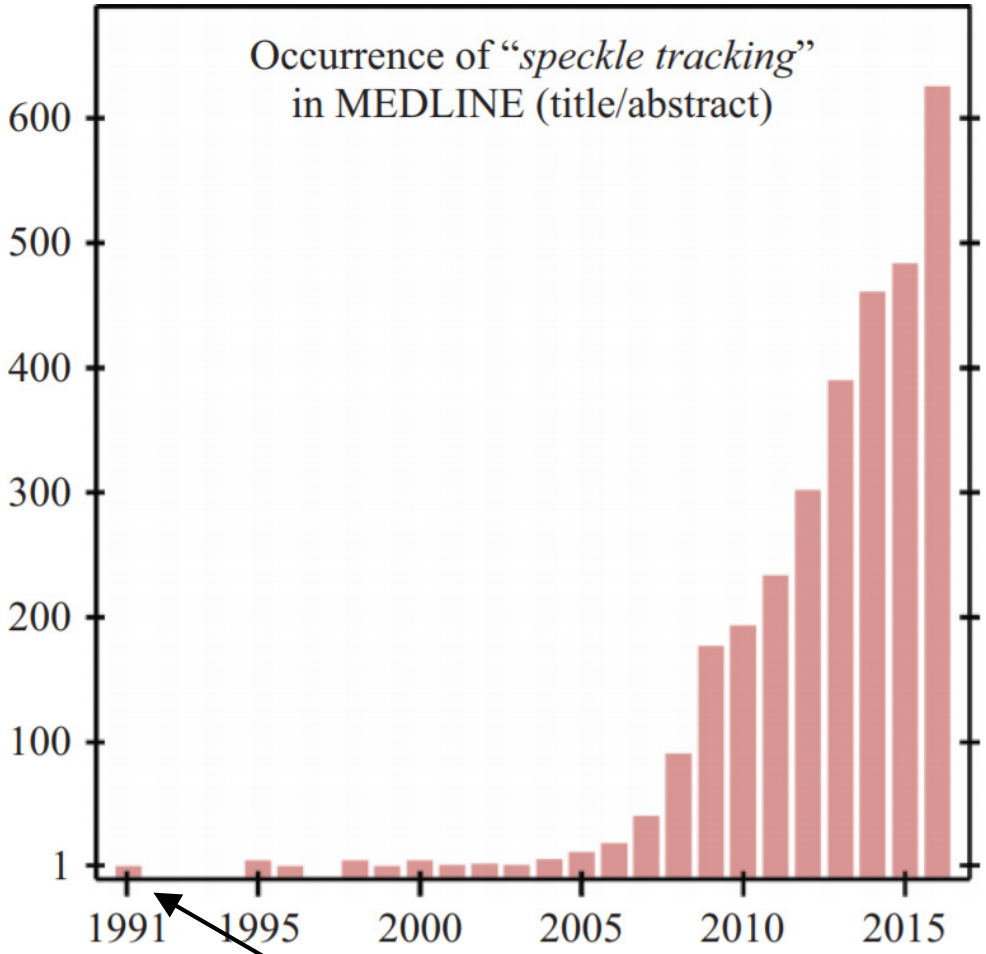
April 25, 2019

Disclaimer: The views expressed in this course are those of the author and do not necessarily reflect the multiple positions of the ultrasound community. The examples may contain errors and can carry an implied judgement due to author's preference for one side of an issue over another.
Be critical and take a step back while reading this document!

TOC

- RF & I/Q & speckles
- algorithms in motion tracking
- block-matching by cross-correlation
- cardiac strain imaging

speckle tracking in medical science

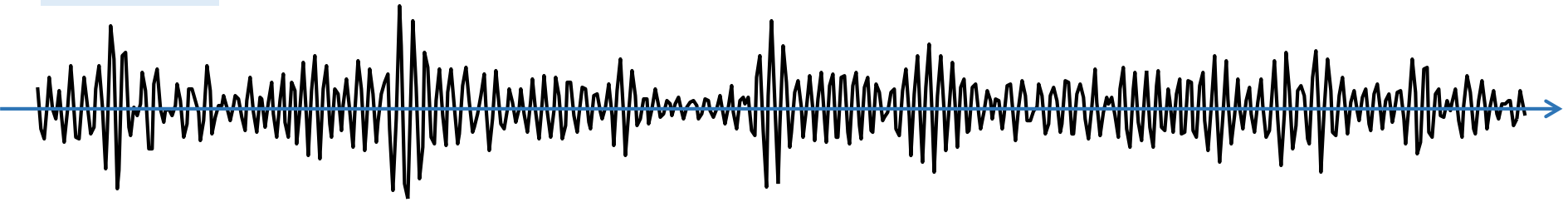


Bohs LN, Trahey GE. A novel method for angle independent ultrasonic imaging of blood flow and tissue motion.
IEEE Trans Biomed Eng. 1991;38(3): 280–6

RF & I/Q & speckles

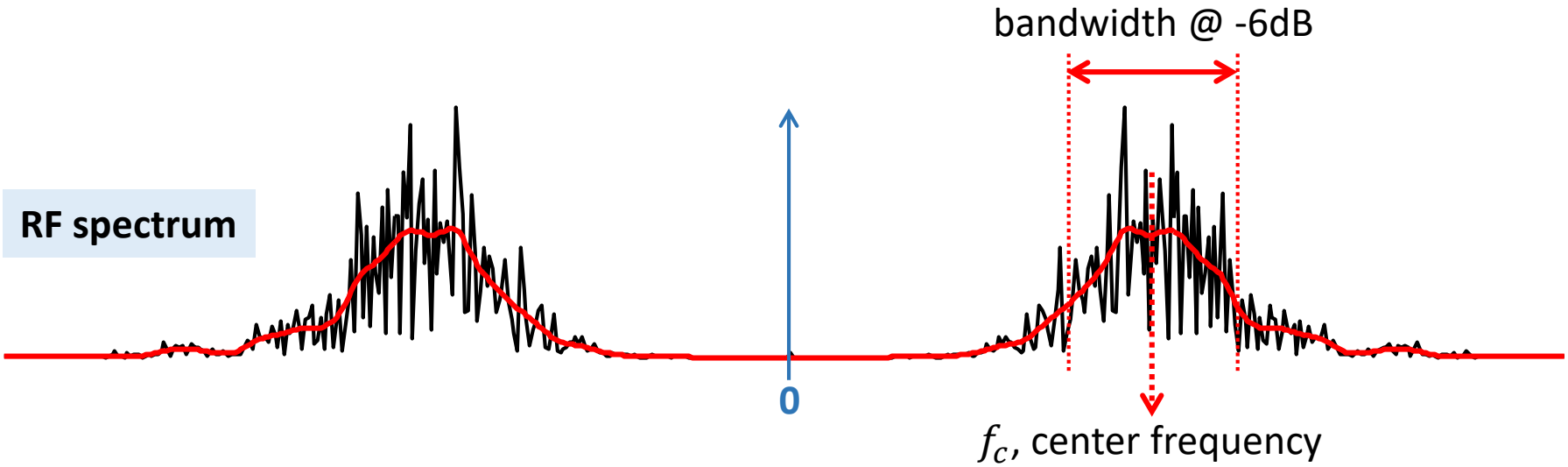
RF signal & its spectrum

RF signal

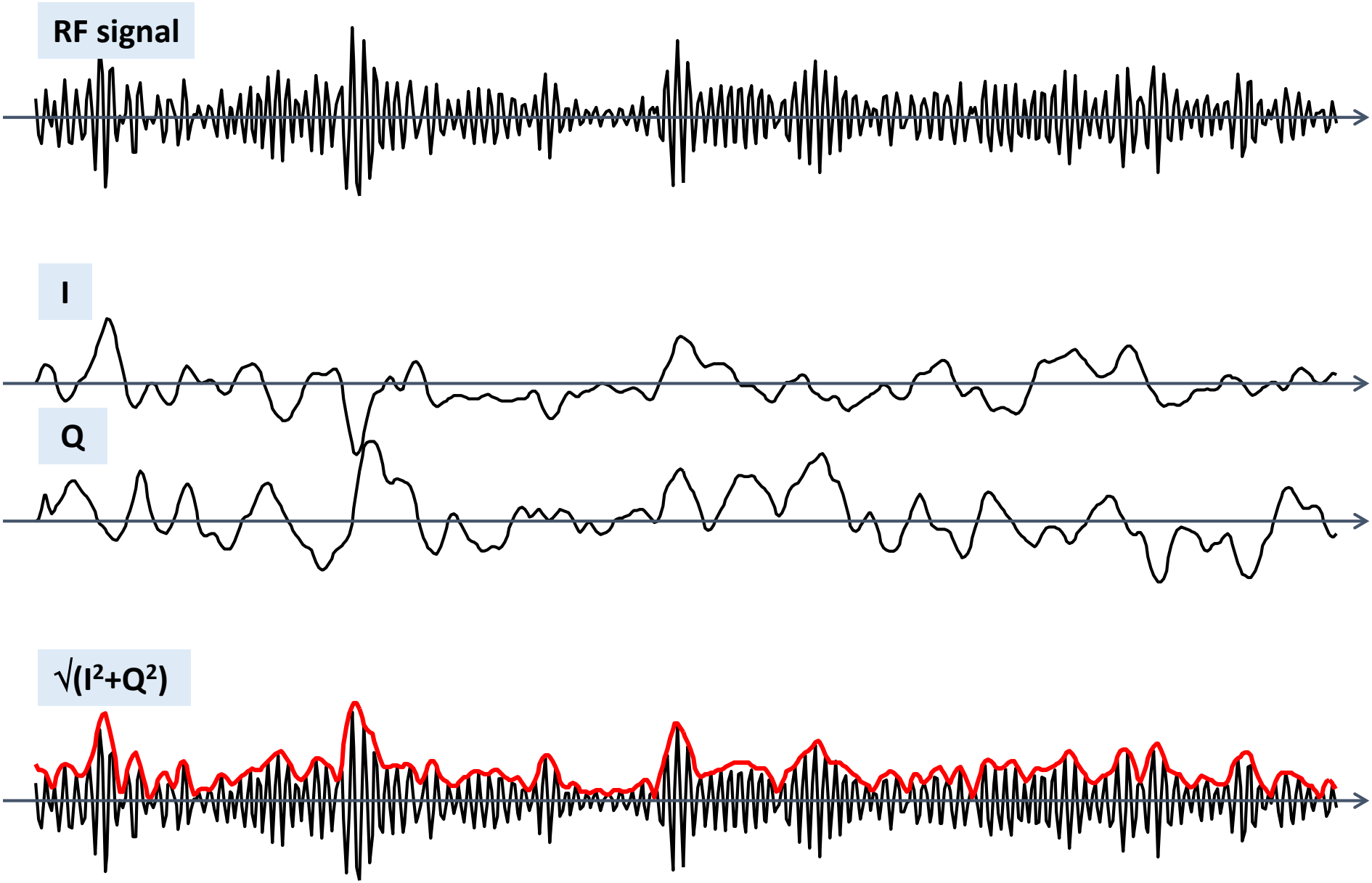


- the ultrasound RF signal is a **band-pass signal**

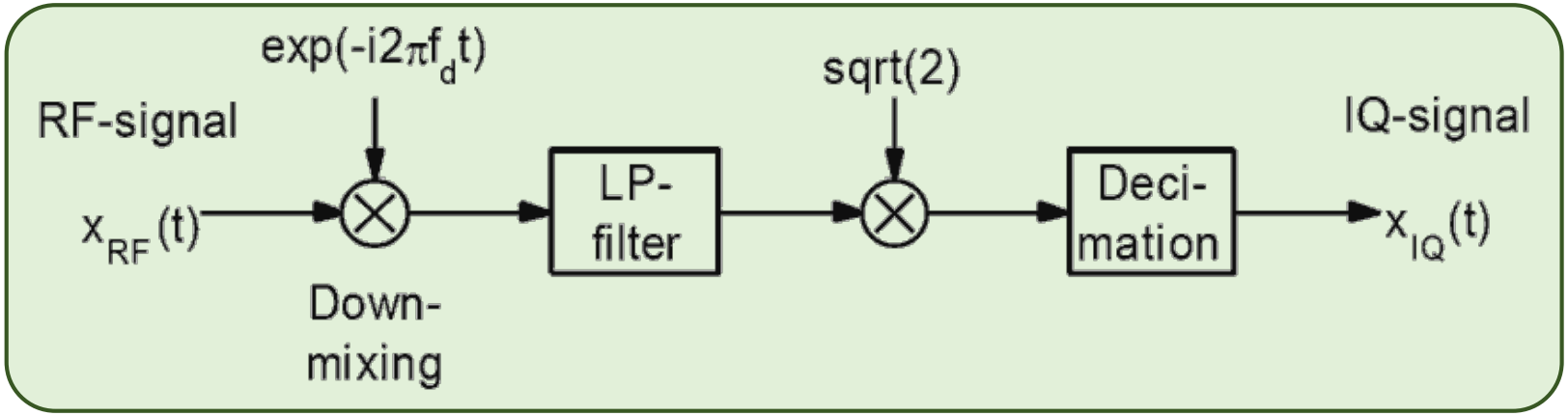
RF spectrum

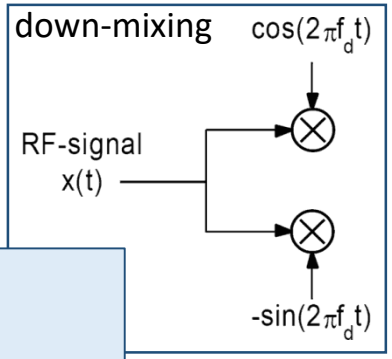


RF *vs.* I/Q signal



I/Q demodulation



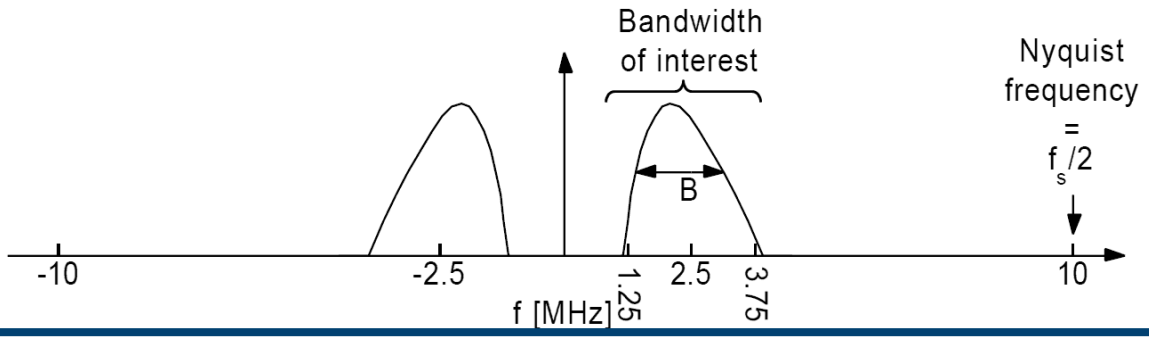


- f_d = demodulation frequency (center frequency)
- LP-filter = low-pass filter
- conservation of signal energy $\Rightarrow$ multiplication by $\sqrt{2}$
- decimation = downsampling

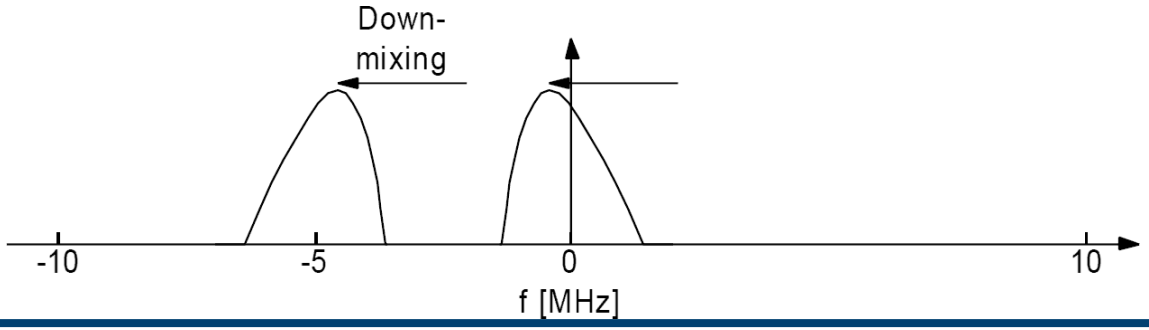
source: Kirkhorn, *Introduction to IQ-demodulation of RF data*. White paper, 1999

I/Q demodulation

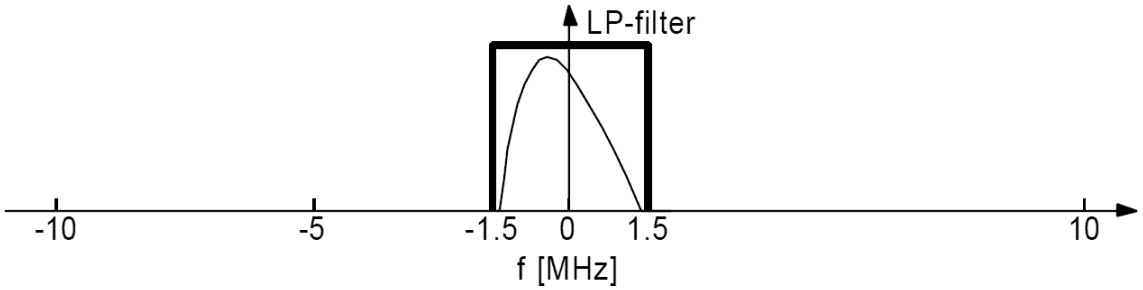
1. RF spectrum



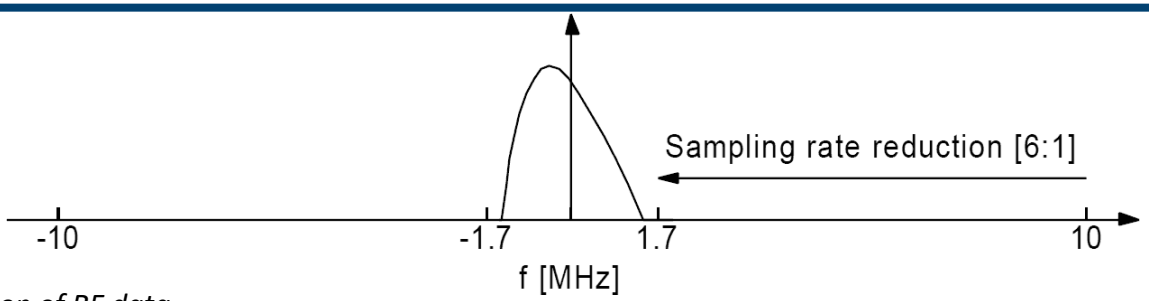
2. Down-mixing



3. Low-pass filtering



4. Decimation



source: Kirkhorn, *Introduction to IQ-demodulation of RF data*.
White paper, 1999

I/Q demodulation

- **I/Q demodulation of RF signals – a 5-line Matlab code**



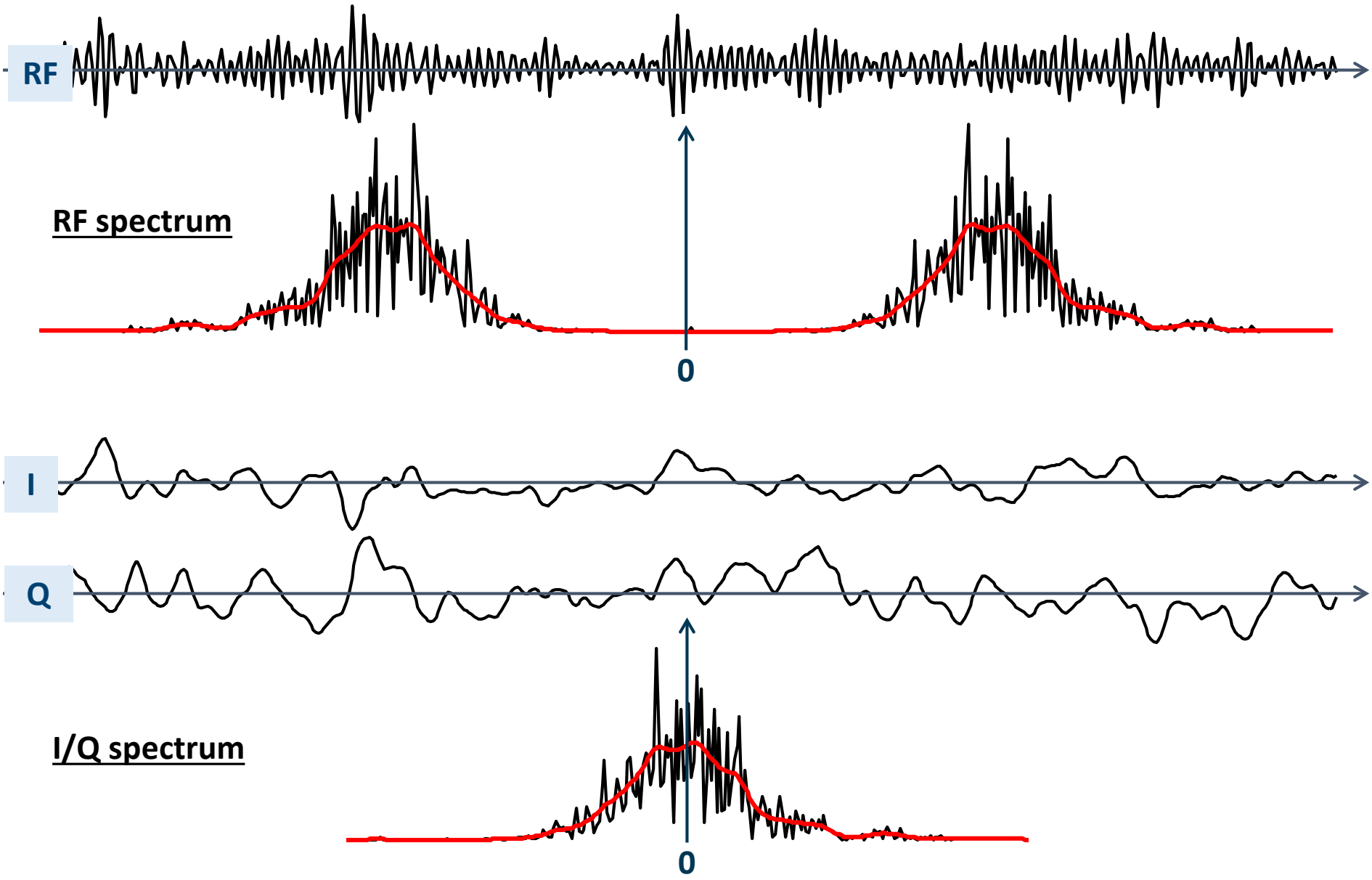
```
%-- RF = RF ultrasound signals
% RF = array whose columns contain the RF signals
% Fs = sampling frequency
% Fc = carrier (center) frequency

%-- Time column vector
N = size(RF,1); % number of time samples
t = (0:N-1)'/Fs;

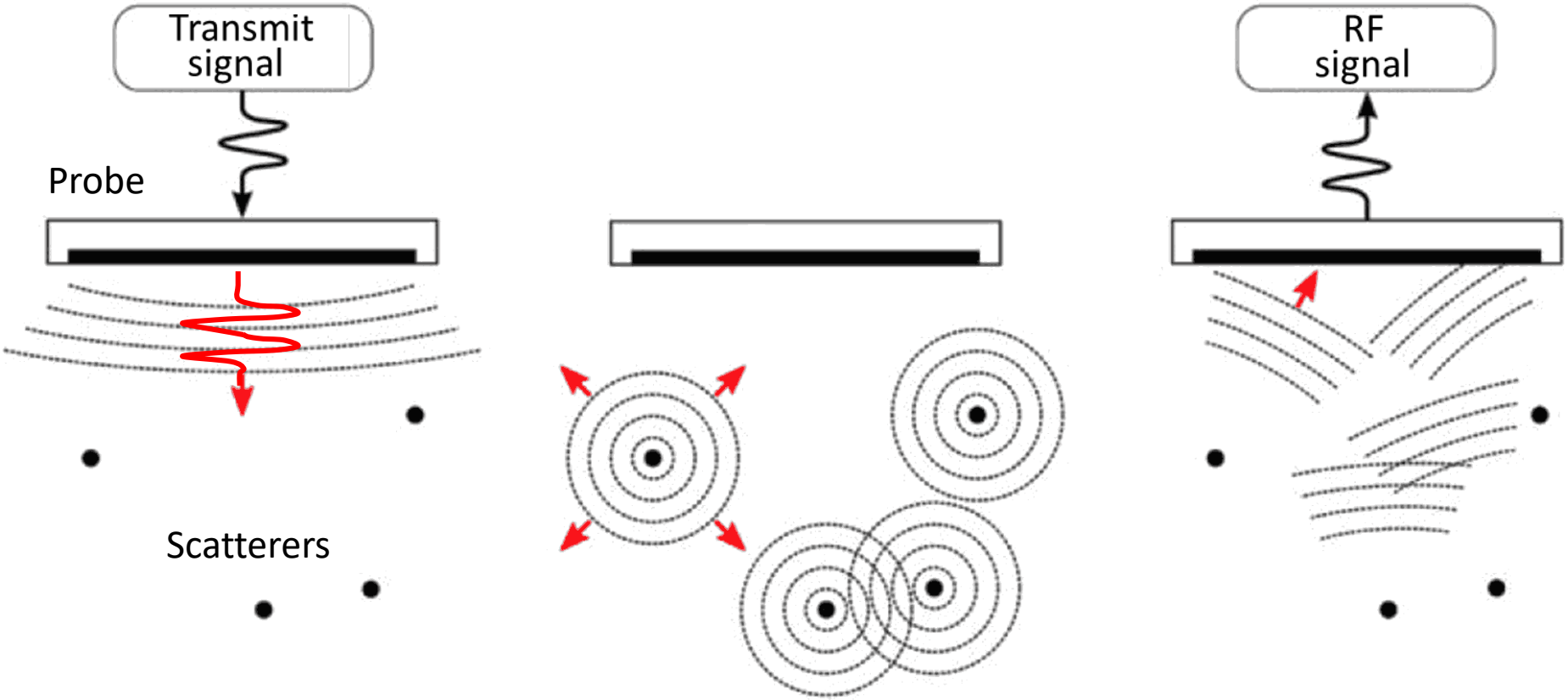
%-- Down-mixing of the RF signals
IQ = RF.*exp(-1i*2*pi*Fc*t); % w/ Matlab version >9.1

%-- Low-pass filter
% IQ = I/Q signals
[b,a] = butter(5,2*Fc/Fs);
IQ = filtfilt(b,a,IQ)*2; % *2 to preserve amplitudes
```

I/Q demodulation: recap

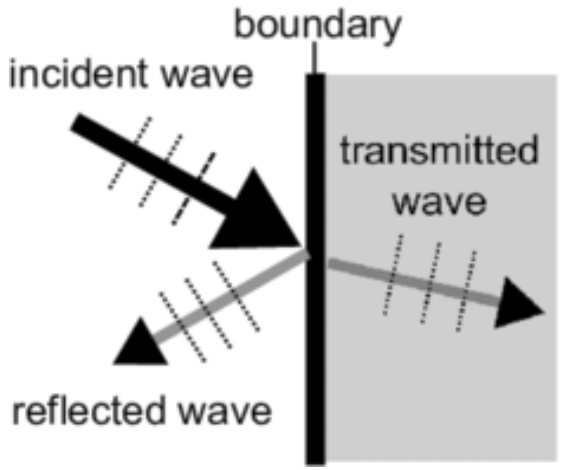


beamforming

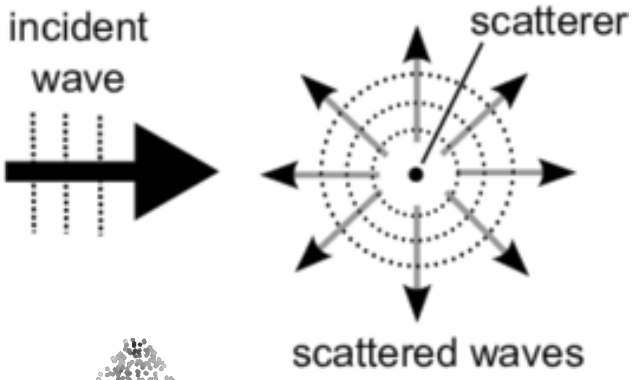


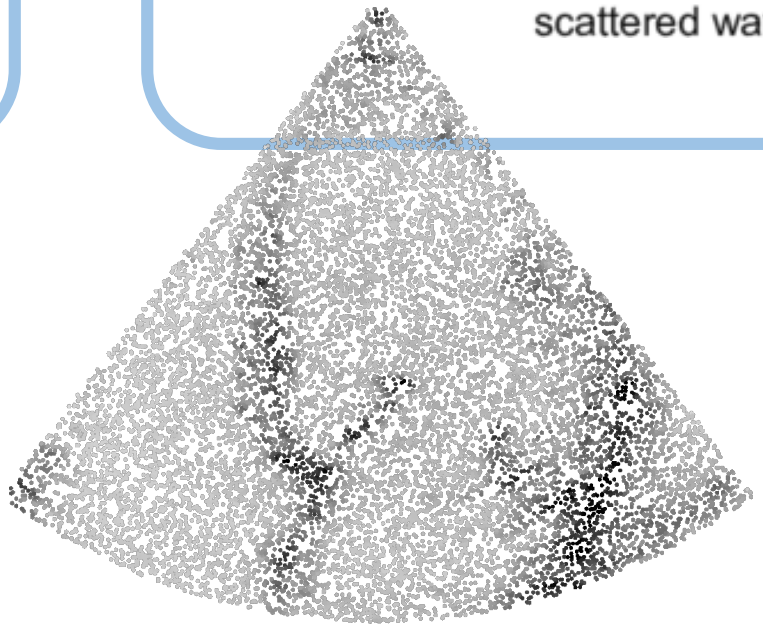
scattering

Specular scattering



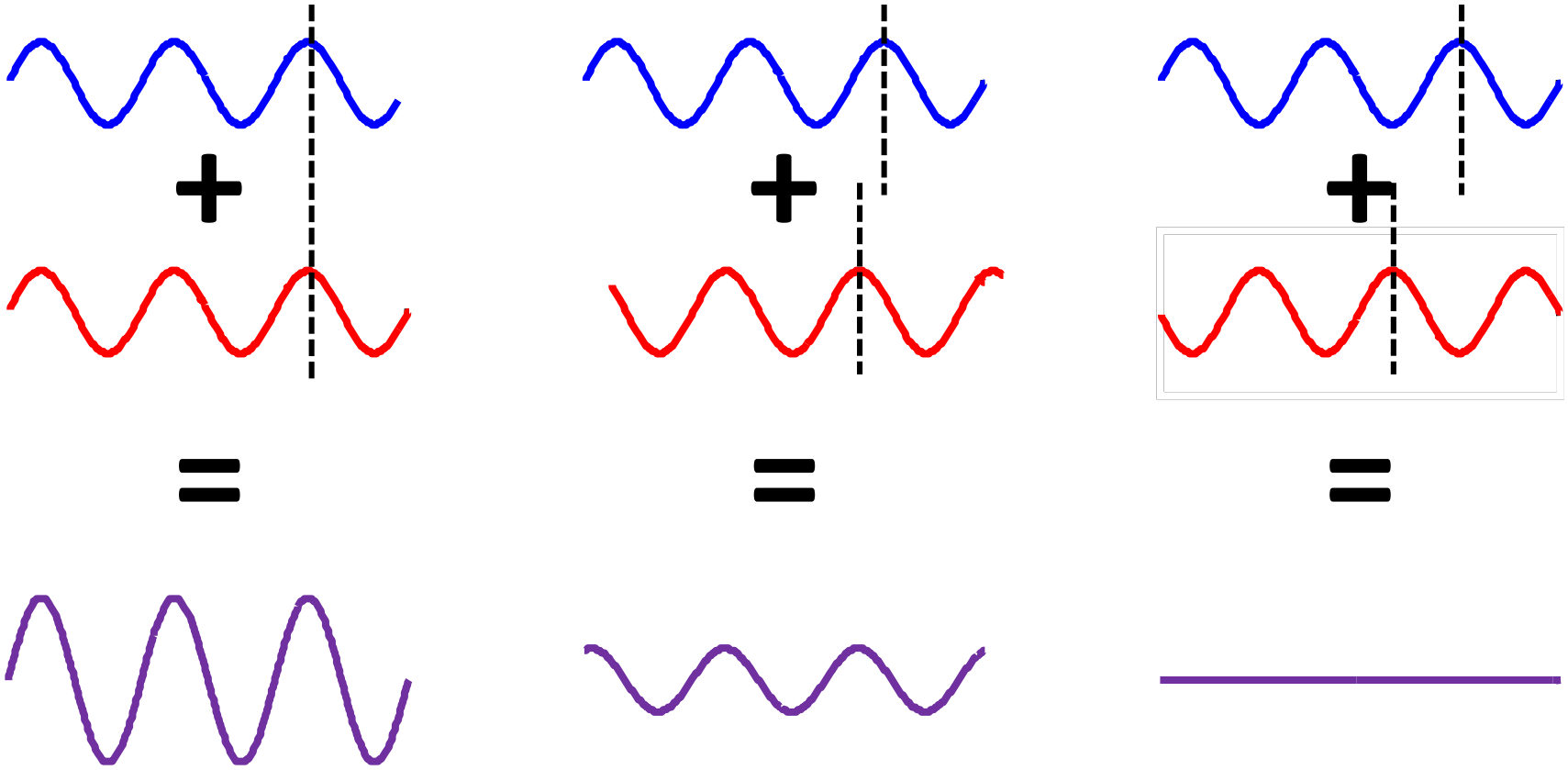
Diffuse (Rayleigh) scattering





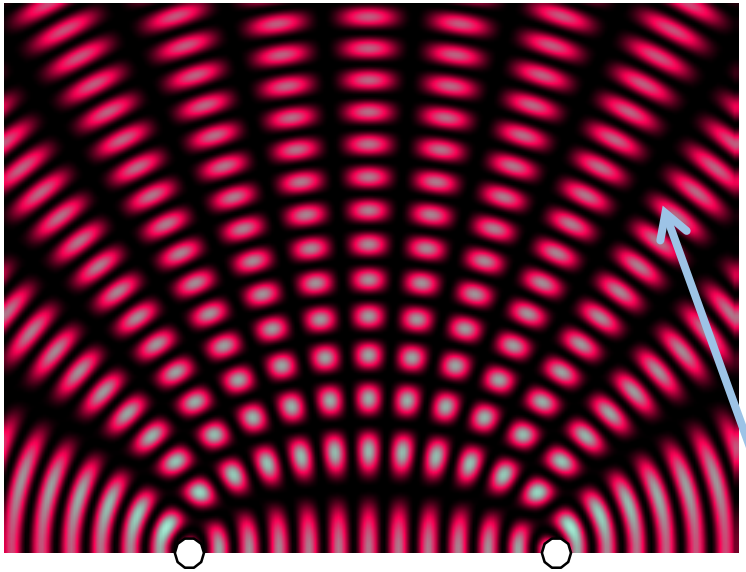
source: doi:10.13140/RG.2.1.3563.2486

constructive & destructive interferences

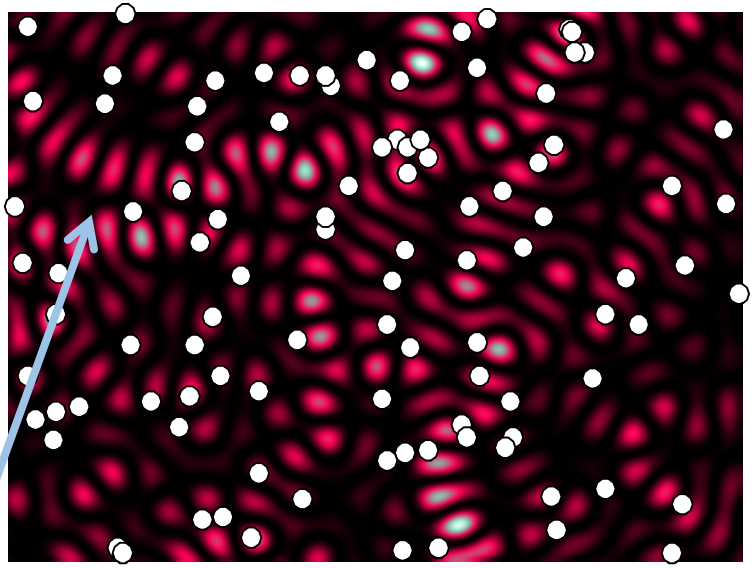


scatterers & speckles

2 scatterers



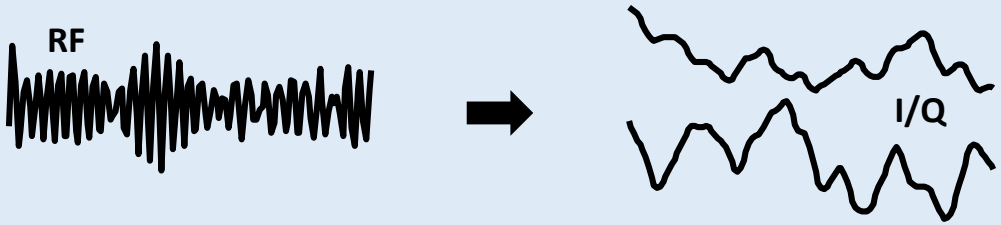
multiple scatterers



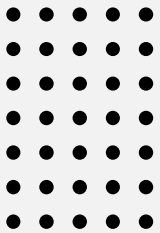
speckles

4 steps to generate a B-mode ultrasound image

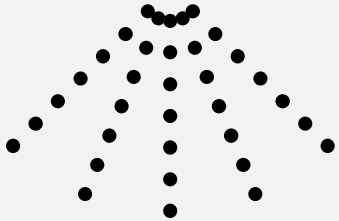
1. Demodulate the received RF signals to obtain I/Q signals



2. Choose a grid for your image



or



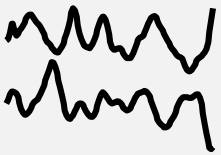
or what you need

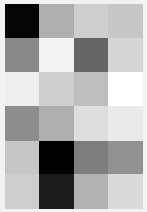
3. Beamform the I/Q signals (e.g. using a delay-and-sum)

```
IQ_beamformed = Mdas*IQ(:);
% Mdas: matrix of size [#grid_points #IQ_samples]
```

4. Take the amplitude then compress to obtain a B-mode image

beamformed **I/Q**

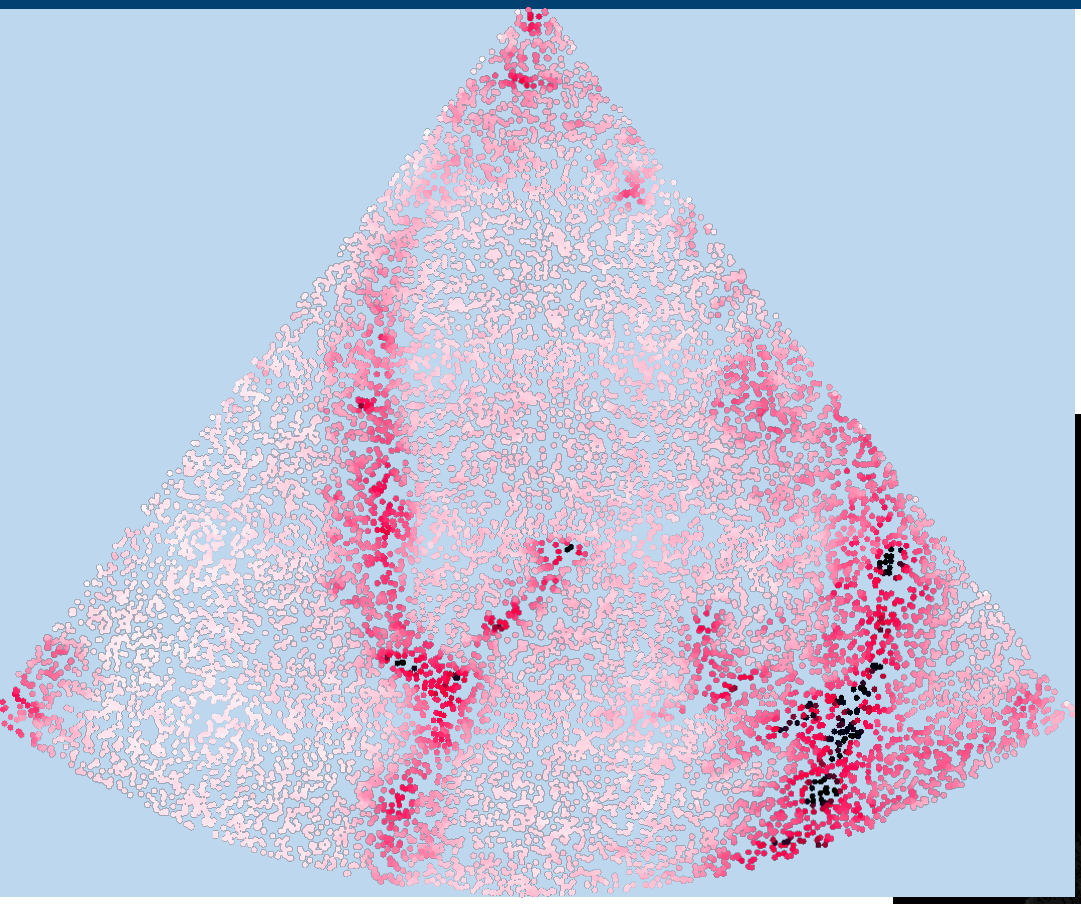


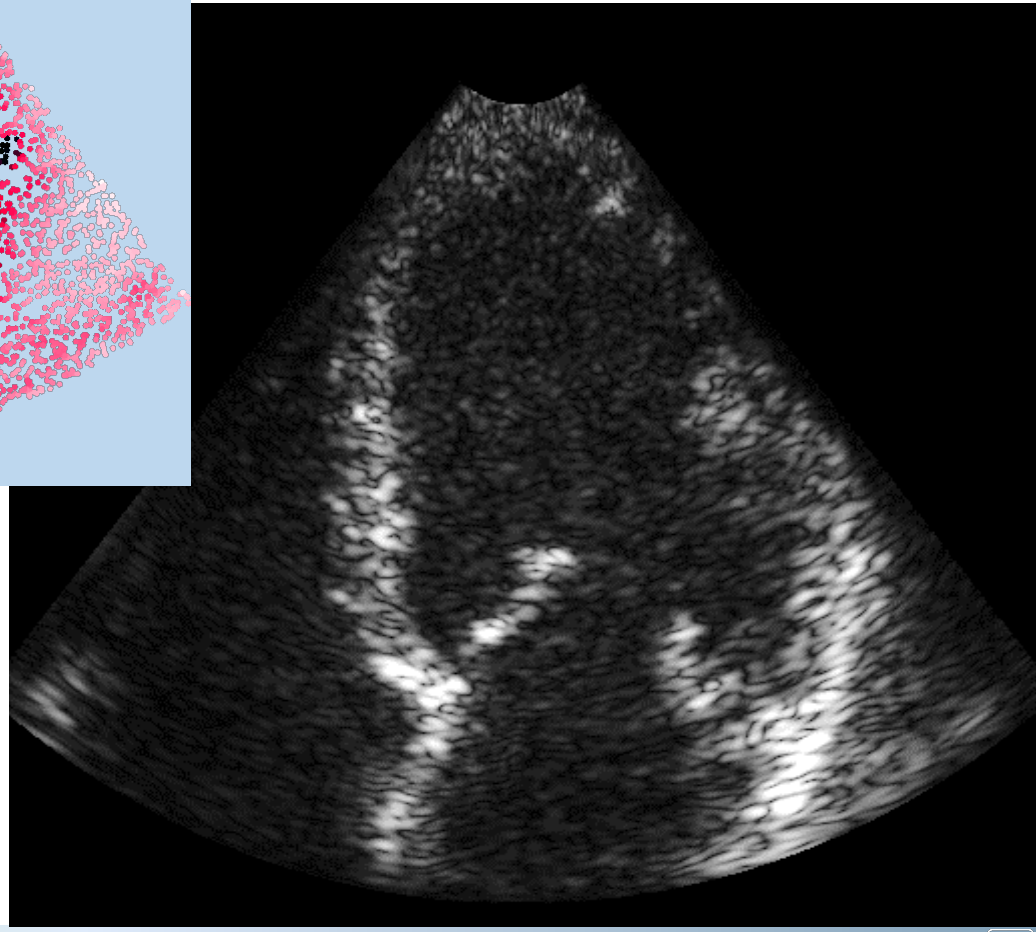


or



scatterers & speckles

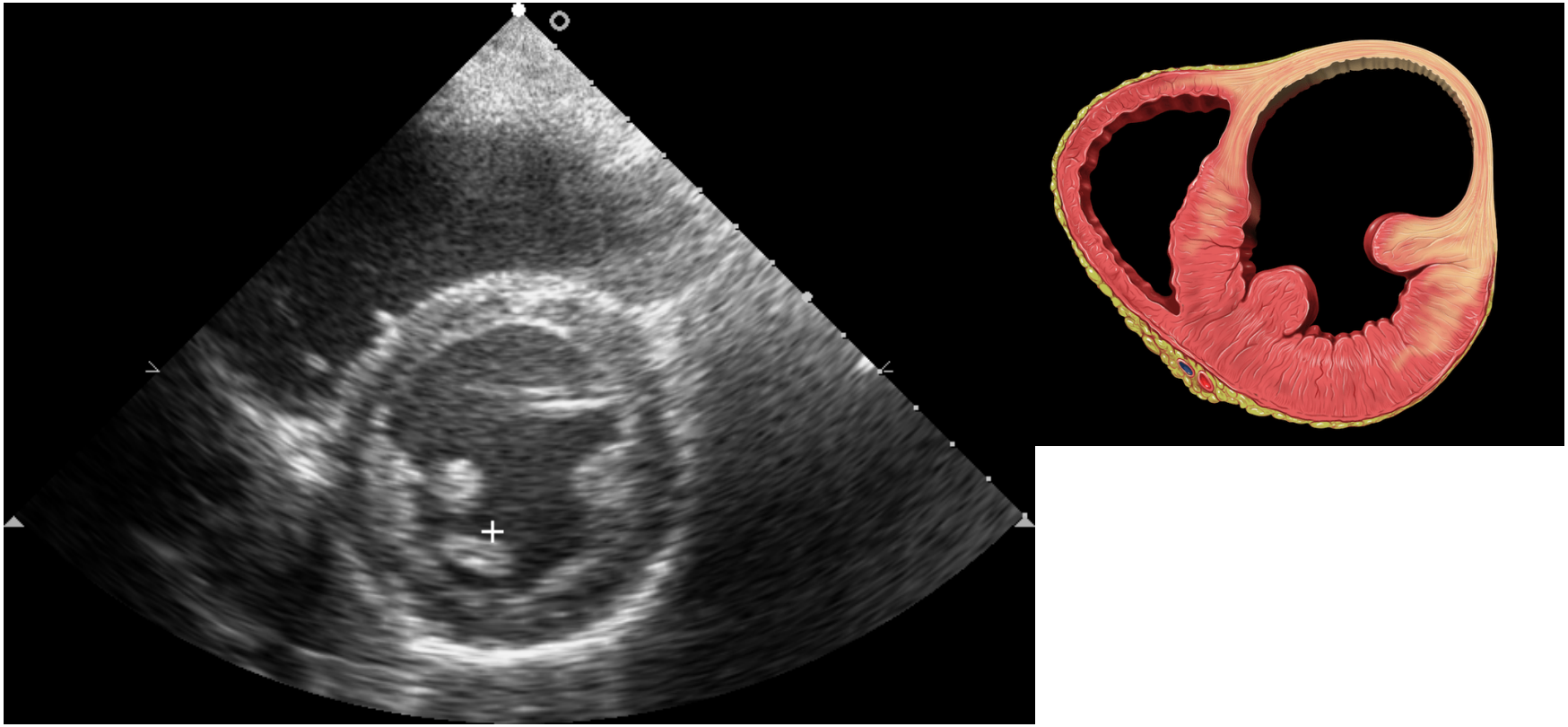




ultrasound B-mode image

- !! the grainy appearance of an ultrasound image is NOT an image of the reflectors present in the tissue !!

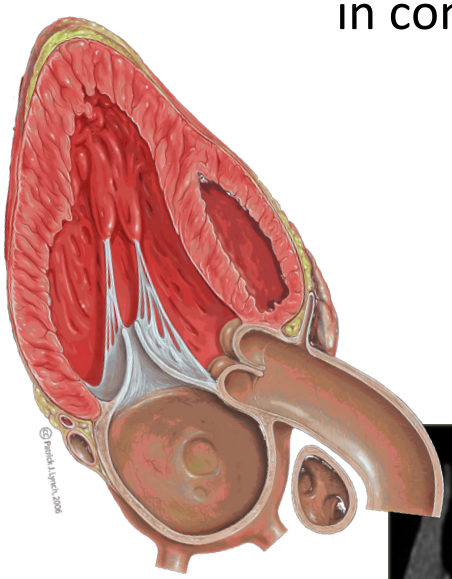
- a B-mode image is an image of the interferences generated by the summation of reflected ultrasonic waves



CMR vs. echocardiography

in comparison with MRI, ultrasound provides “lower” image quality;

BUT real-time, thus EASES MOTION QUANTIFICATION.

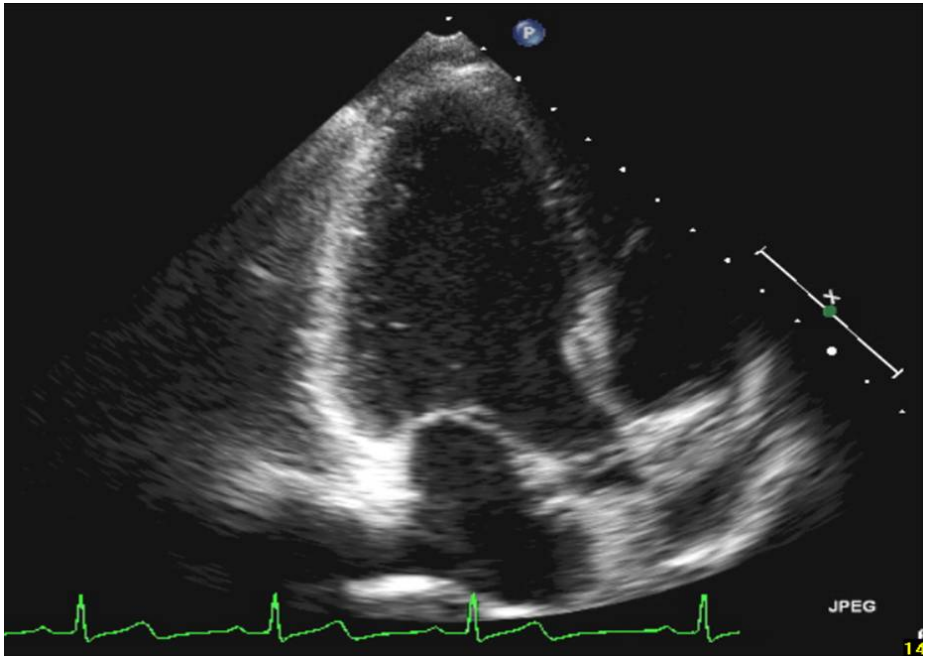


CMR



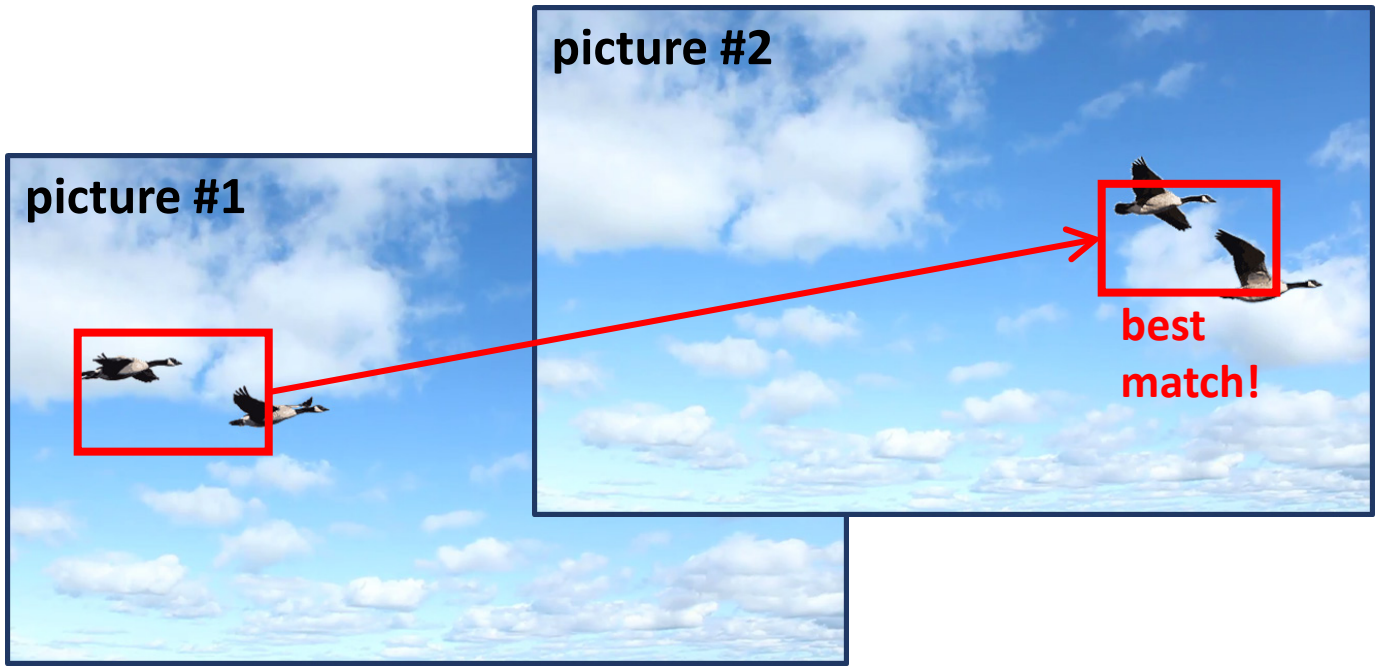


Echo



algorithms in motion tracking

motion tracking



motion tracking: different algorithms

(this list is not exhaustive!)

intensity- or feature-based

1. **intensity**: compare intensity patterns using metrics (e.g. correlation, SAD…)
2. **feature**: find correspondences (often points or contours)

local or global

1. **local**: find local correspondences, e.g. by using subwindows
2. **global**: find a global correspondence, e.g. by using a least-squares method

linear or nonrigid

1. **linear**: transformations are assumed linear (translation, rotation, scaling…)
2. **nonrigid**: transformations are assumed elastic (“smooth” deformations)

spatial or frequency domain

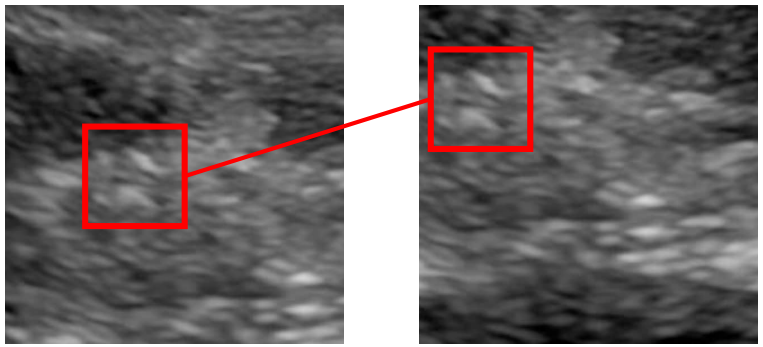
1. **spatial**: algorithm in the image domain
2. **frequency**: find transformations in the Fourier domain

intensity- or feature-based

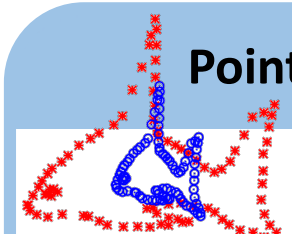
1. **intensity**: compare intensity patterns using metrics (e.g. correlation, SAD…)
2. **feature**: fid correspondences (often points or contours)

- Most of the tracking algorithms in ultrasound imaging are **intensity-based**.

Speckle intensity

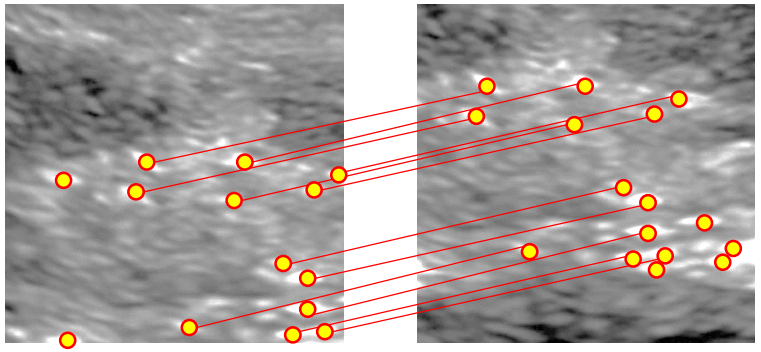


Point-set registration



https://en.wikipedia.org/wiki/Point_set_registration

source: Widynski, Géraud, Garcia.
doi: 10.1109/ULTSYM.2014.0430

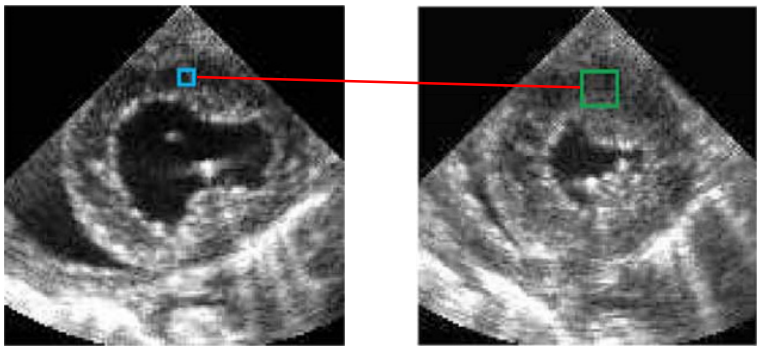


local *vs*. global in ultrasound imaging

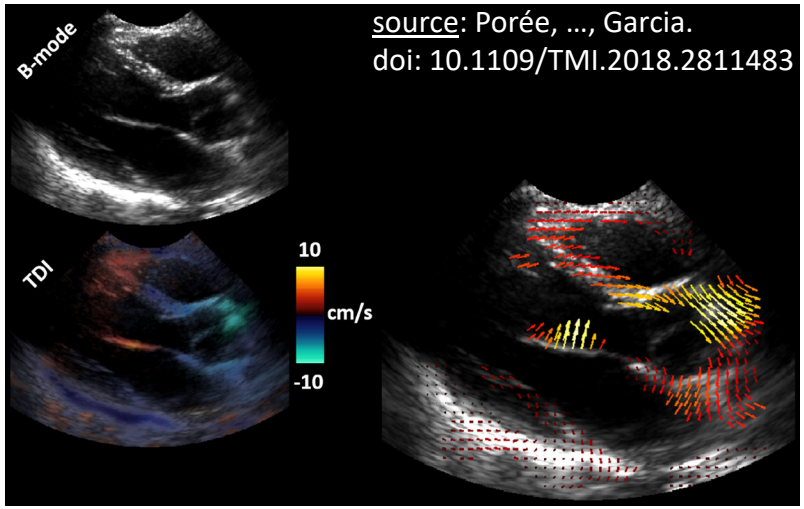
local or global

1. **local**: find local correspondences, e.g. by using subwindows
2. **global**: find a global correspondence, e.g. by using a least-squares method

Local



Global (least-squares)

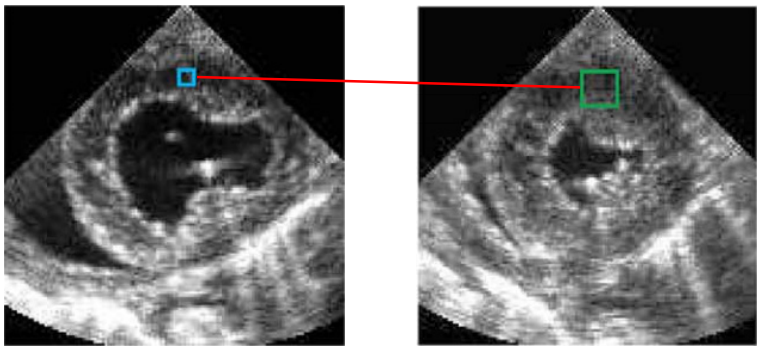


source: Porée, …, Garcia.
doi: 10.1109/TMI.2018.2811483

linear or nonrigid

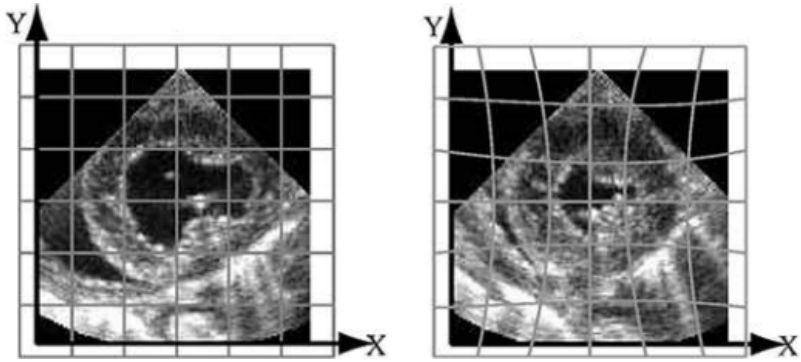
1. **linear**: transformations are assumed linear (translation, rotation, scaling…)
2. **nonrigid**: transformations are assumed elastic (“smooth” deformations)

Linear (translation)



Nonrigid (elastic)

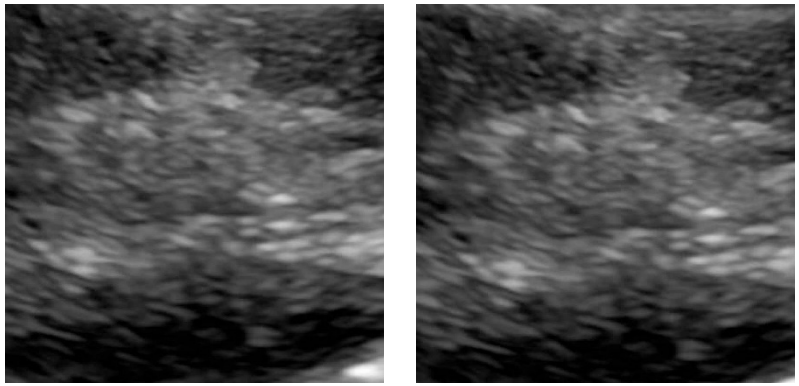
source: Heyde, …, D’hooge.
doi: 10.1109/TMI.2012.2230114



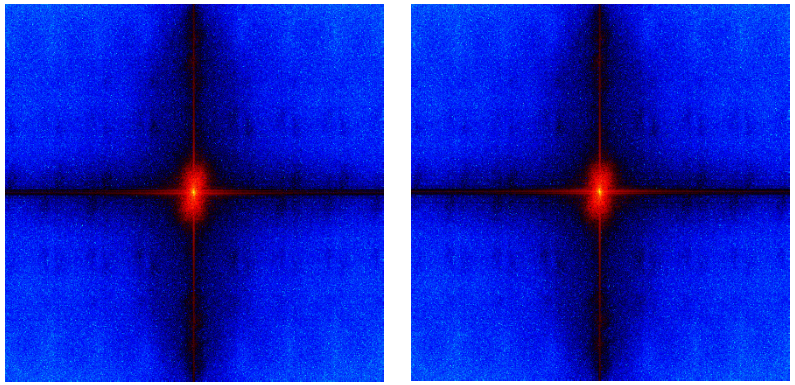
spatial or frequency domain

1. **spatial**: algorithm in the image domain
2. **frequency**: find transformations in the Fourier domain

Spatial domain



Fourier domain



white box *vs*. black box in ultrasound imaging

white box or black box

1. **white box**: the algorithm is known
2. **black box**: no (or very little) knowledge of the algorithm (e.g. deep learning)

- It is likely that CNN-based motion tracking will become popular.

White box

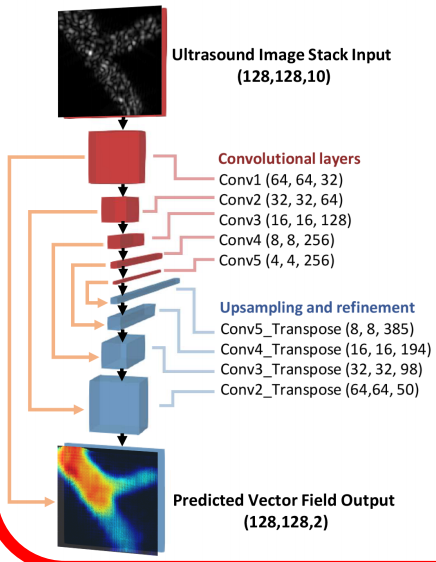
```
%-- I1, I2: two successive images
% [m n] = size of the blocks
[M,N] = size(I1);
D = NaN(ceil(M/m),ceil(N/n),'like',1i); % mem allocation

I1blk = im2col(I1,[m n],'distinct'); % convert to blocks

for k = 1:size(I1blk,2)
   Bk = reshape(I1blk(:,k),[m n]); % block matrix #k
   C = normxcorr2(Bk,I2); % normalized X-correlation
   [i2,j2] = find(C==max(C(:)),1); % peak location
   % ADD sub-pixel estimator HERE

   i1 = m*mod(k-1,ceil(M/m))+m; % original location
   j1 = n*(k-i1/m)/ceil(M/m)+n; % original location
   D(k) = complex(i2-i1,j2-j1); % displacement
end
```

Black box (deep neural network)



source: Robins, …, Tang.
arXiv: 1903.06254

SA-VFI 2018 challenge

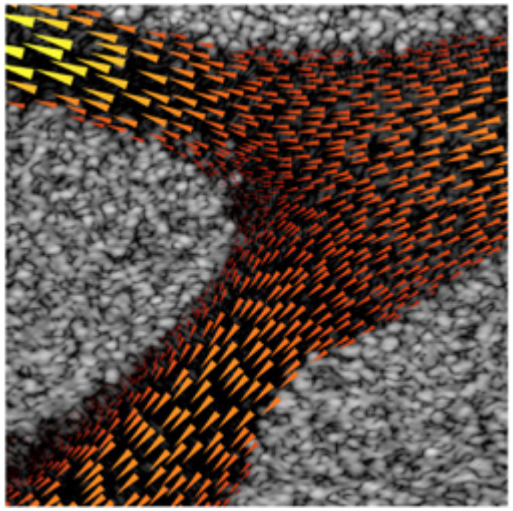
- During the hands-on session, you will use a fast algorithm that calculates subwindow cross-correlations in the Fourier domain

⇒ **intensity**-based, **local**, **linear** (translations), **frequency** domain





winner of the SA-VFI challenge, IUS Kobe 2018



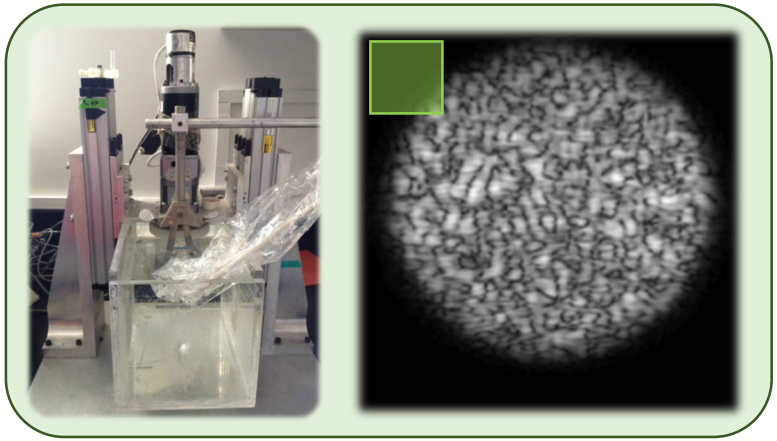
key paper

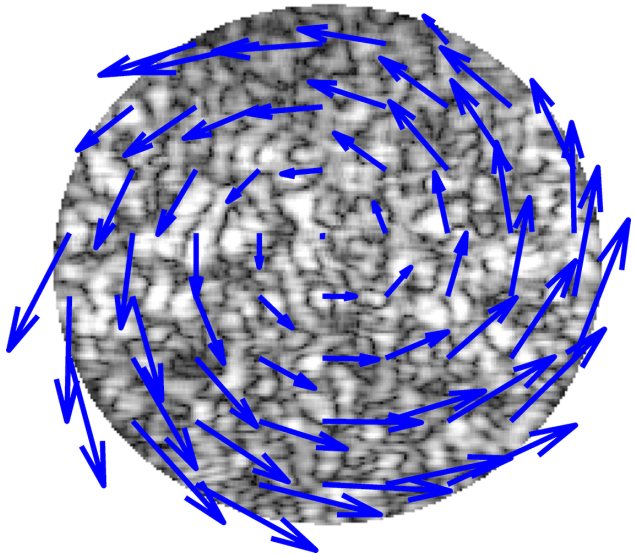
- Perrot *et al*. IUS 2018.
  doi:10.1109/ULTSYM.2018.8579665

https://ieee-uffc.org/news/synthetic-aperture-vector-flow-imaging-challenge-ius-2018

block-matching by cross-correlation





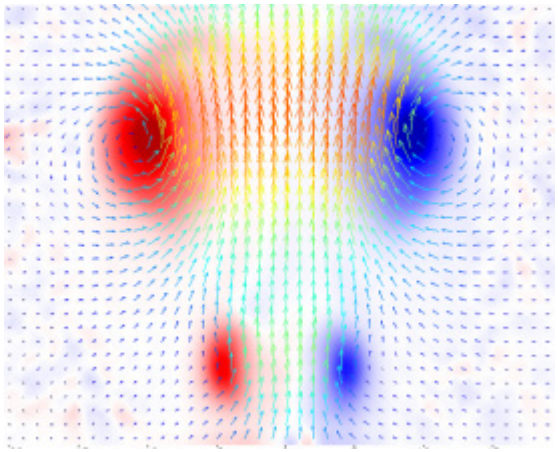


Note: Evaluation metrics other than X-correlation can also be used:

1. SAD: Sum of Absolute Differences
2. SSE: Sum of Squared Errors

optical Particle Image Velocimetry

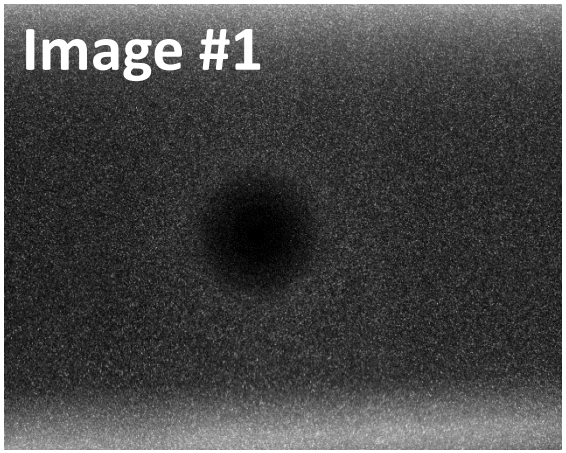
- Although it is often forgotten by the ultrasound community, much can be found in optical PIV (“particle image velocimetry”)
- “PIV is an optical method of flow visualization used in research. It is used to obtain instantaneous velocity measurements in fluids. The fluid is seeded with tracer particles which, for sufficiently small particles, are assumed to follow the flow dynamics” (*Wikipedia*)

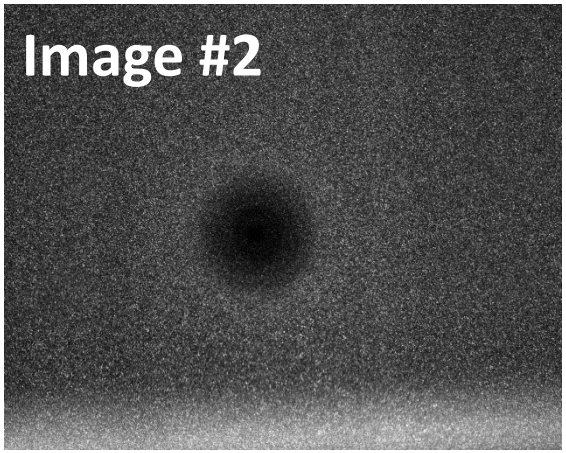


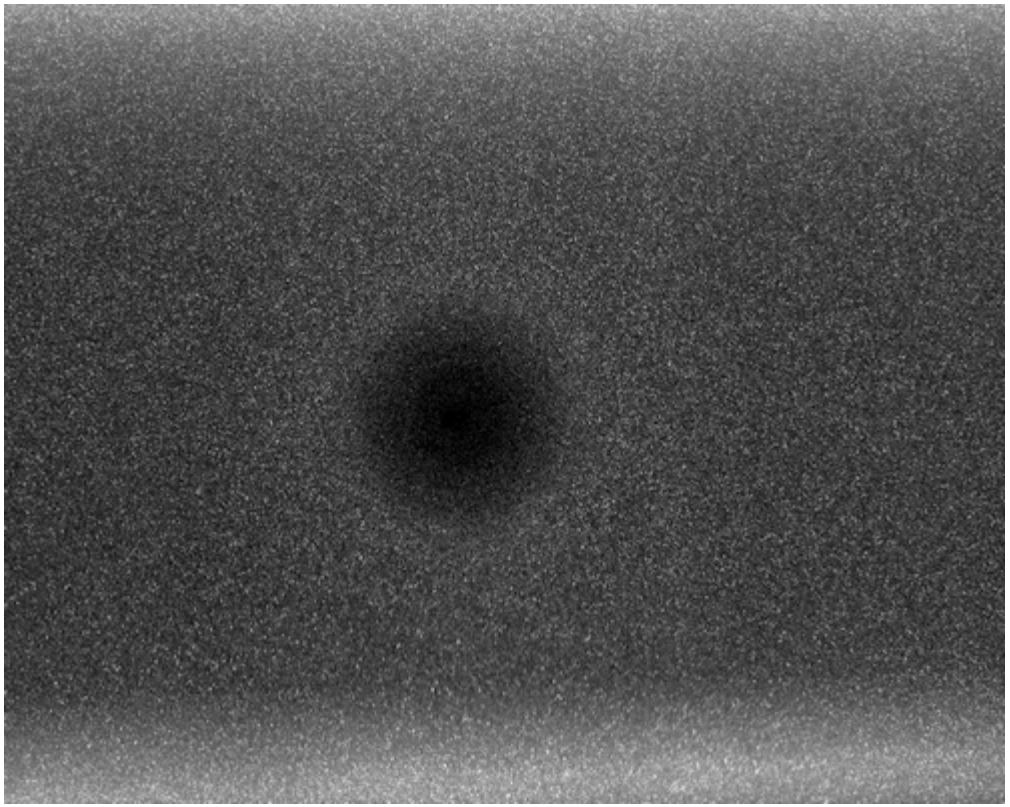


source: www.lavision.de/en/techniques/piv-ptv/

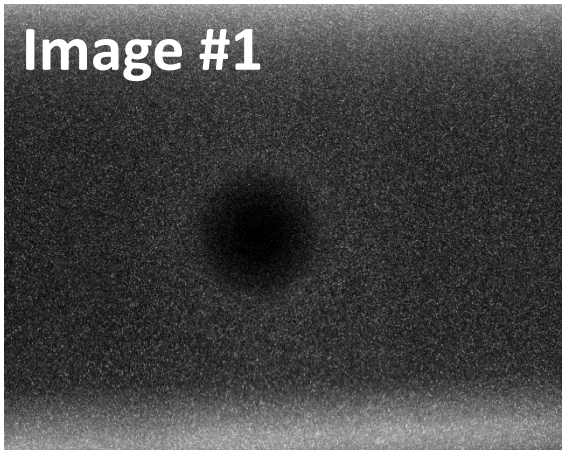
optical PIV: example

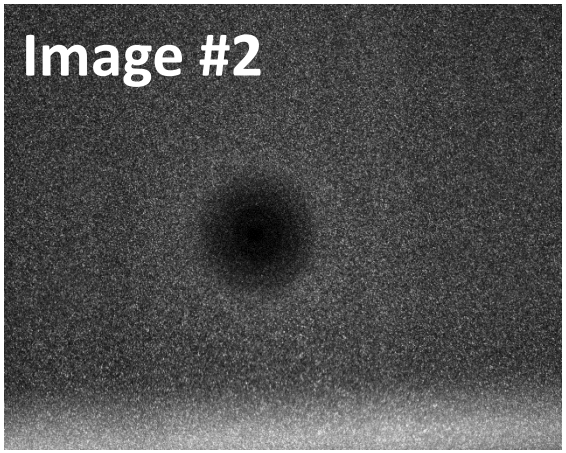


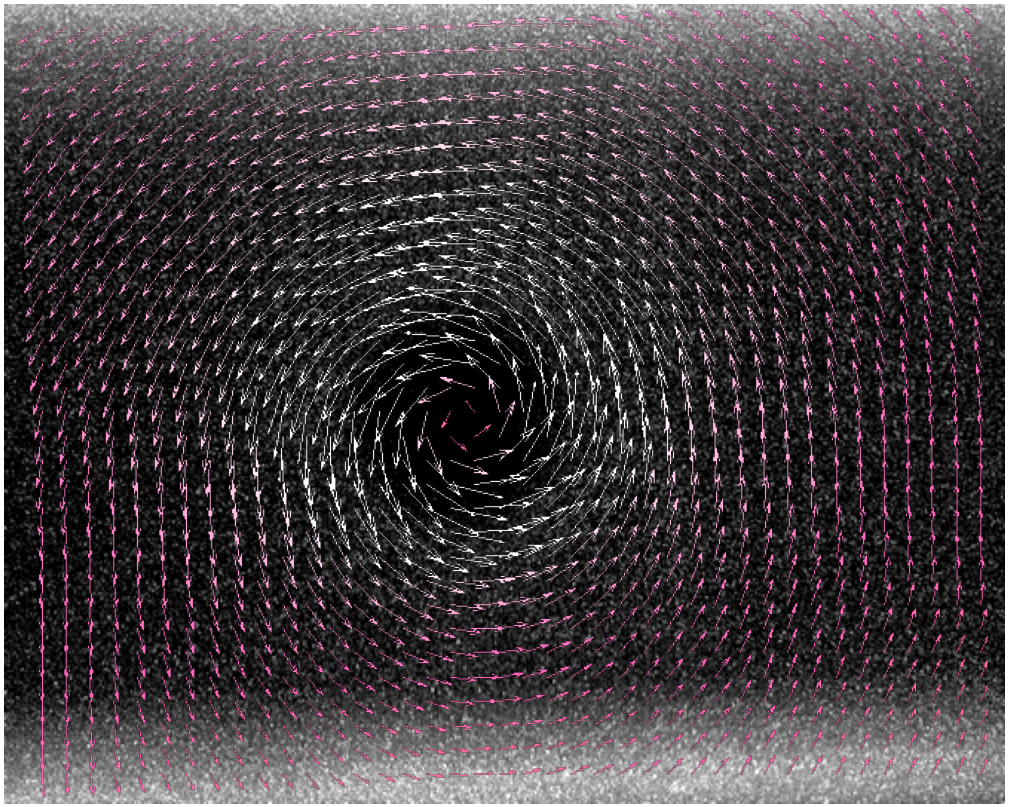




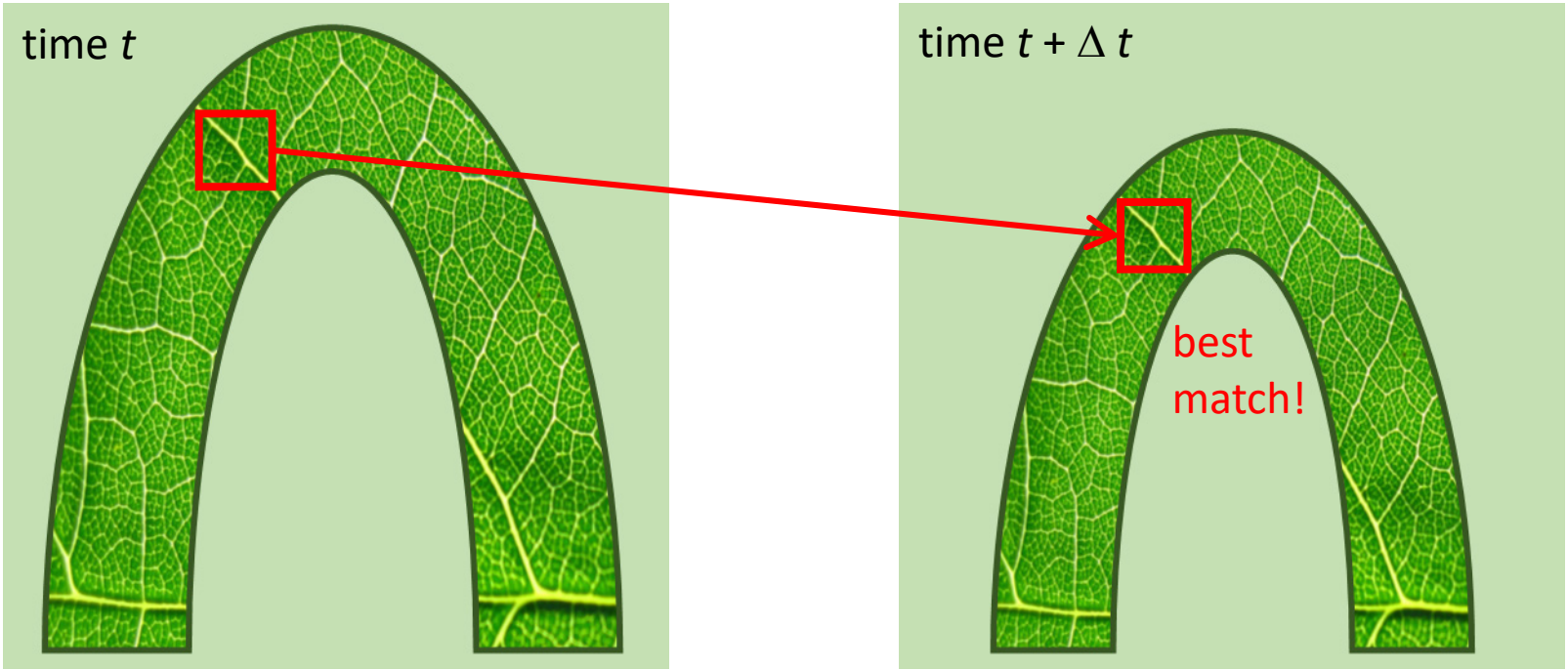
optical PIV: example



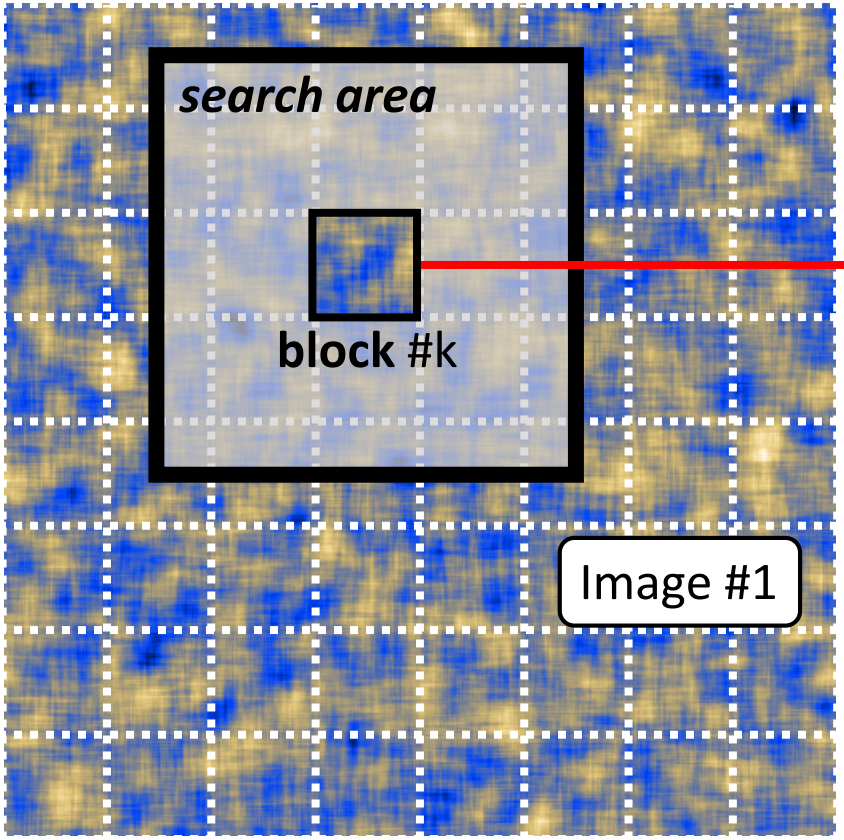


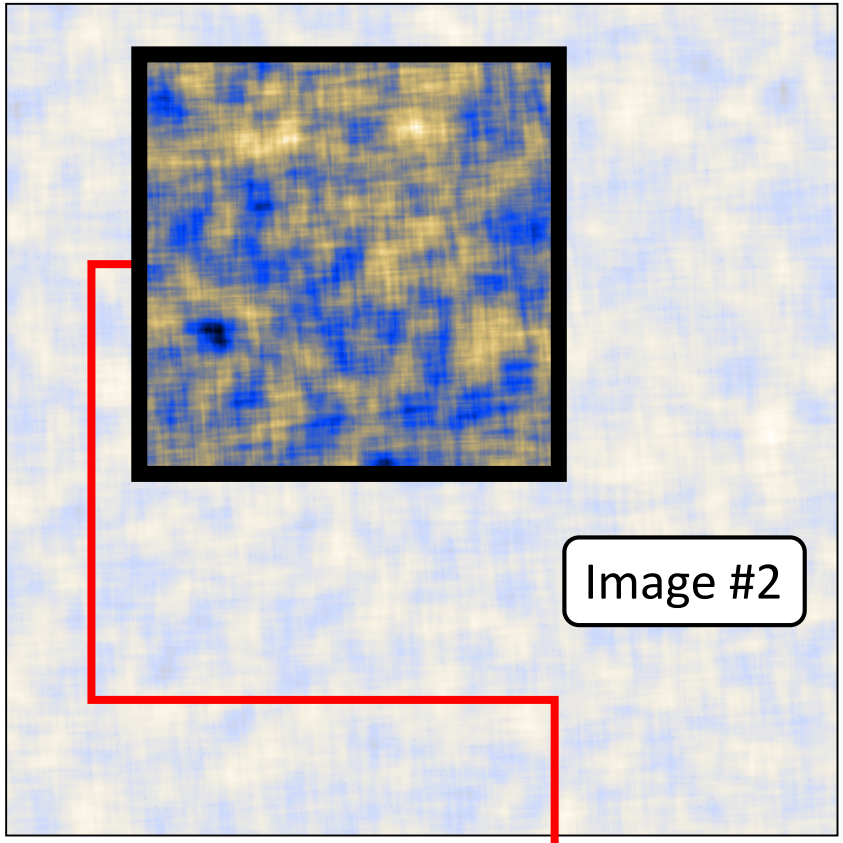


- Same concept in ultrasound imaging…
- The most widely used algorithm is based on block-matching, as in optical PIV



block-matching – basic principles

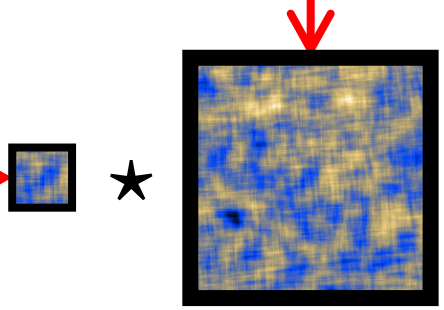




a) **Image #1 is subdivided into blocks**
(the blocks can overlap)

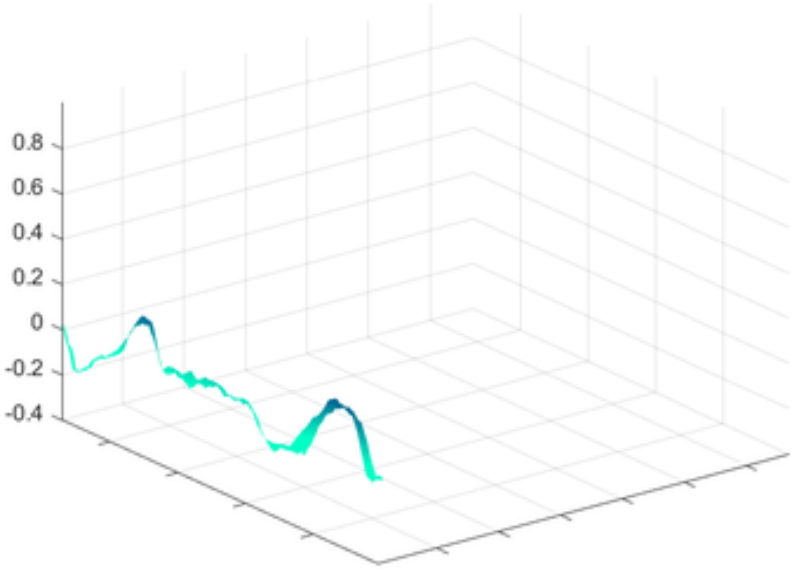
b) **Block** #k **is searched in Image #2**
(inside a surrounding search area)

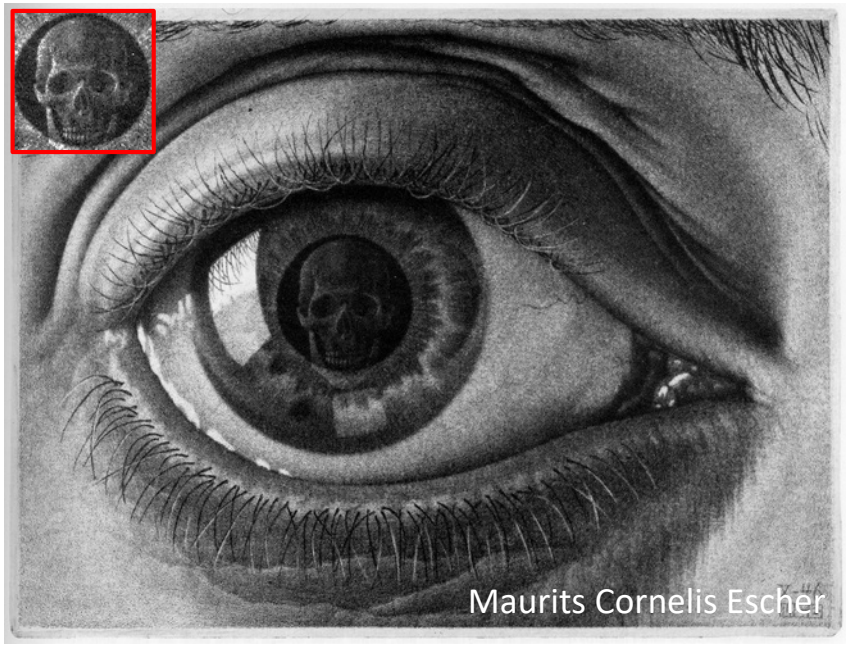
c) **Repeat for** k = 1 … (*number of blocks*)



Normalized cross-correlation

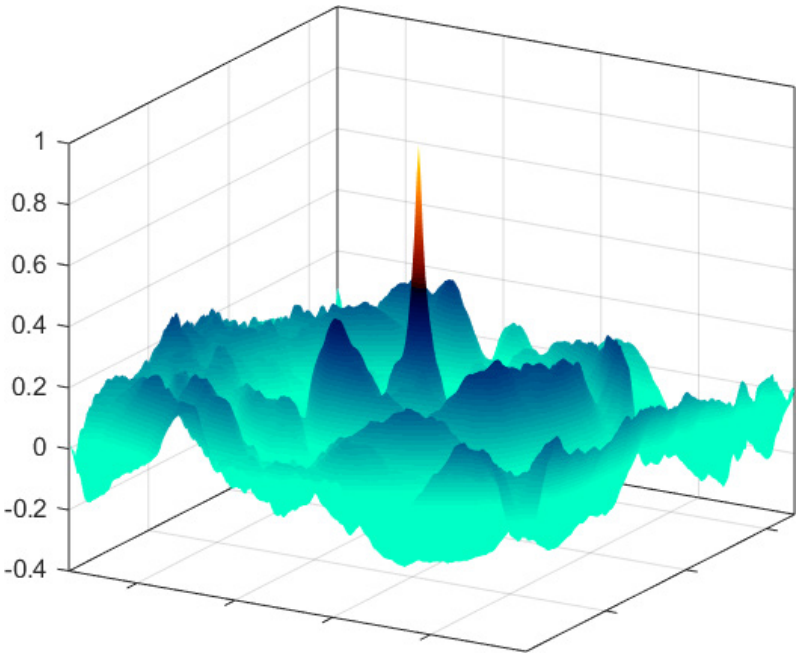
skull-matching by X-correlation

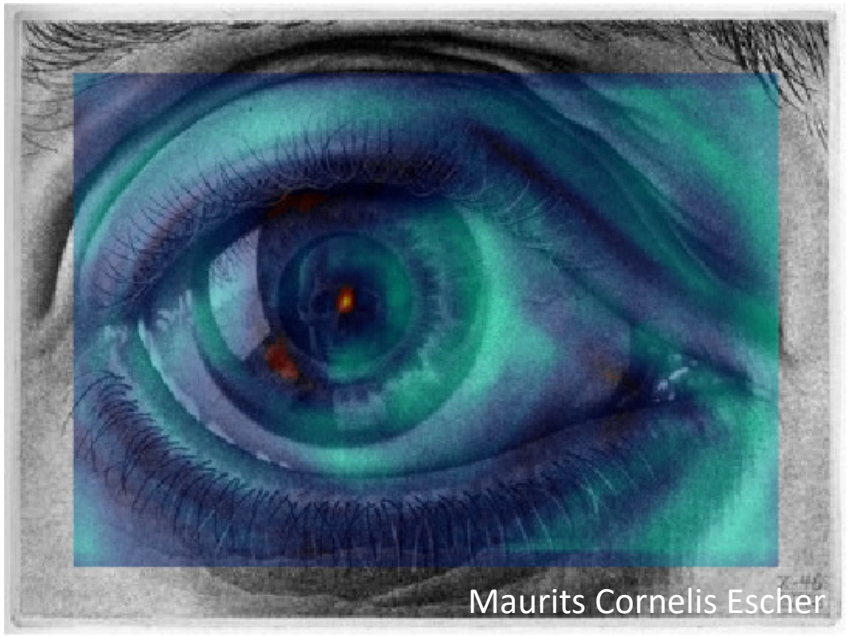






skull-matching by X-correlation







- **block-matching using X-correlation – a *non-optimized* simplified code**



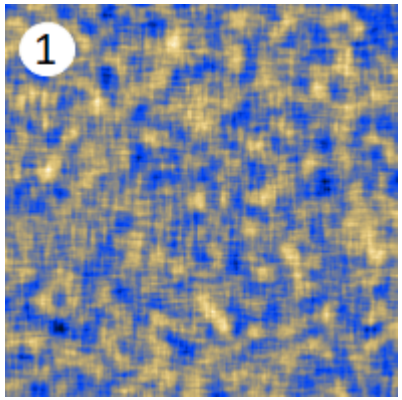
```
%-- I1, I2: two successive images
% [m n] = size of the blocks
[M,N] = size(I1);
D = NaN(ceil(M/m),ceil(N/n),'like',1i); % mem allocation

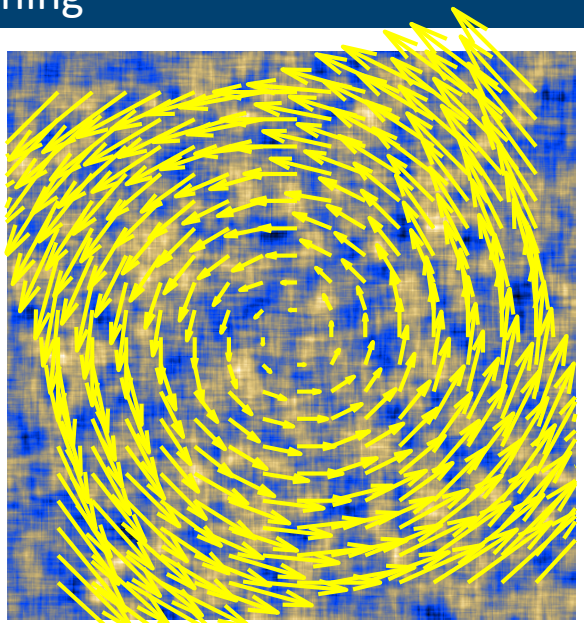
I1blk = im2col(I1,[m n],'distinct'); % convert to blocks

for k = 1:size(I1blk,2)
    Bk = reshape(I1blk(:,k),[m n]); % block matrix #k
    C = normxcorr2(Bk,I2); % normalized X-correlation
    [i2,j2] = find(C==max(C(:)),1); % peak location
    % ADD sub-pixel estimator HERE

    i1 = m*mod(k-1,ceil(M/m))+m; % original location
    j1 = n*(k-i1/m)/ceil(M/m)+n; % original location
    D(k) = complex(i2-i1,j2-j1); % displacement
end
```

block-matching





⚠ **The previous slide describes a simple Matlab code!** ⚠

Must be included:

1. **Limit the size of the search area**
2. **Sub-pixel estimation** (e.g. using peak fitting of the correlation)
3. Removal of the outlying vectors (e.g. using a basic median filter)

Should be included:

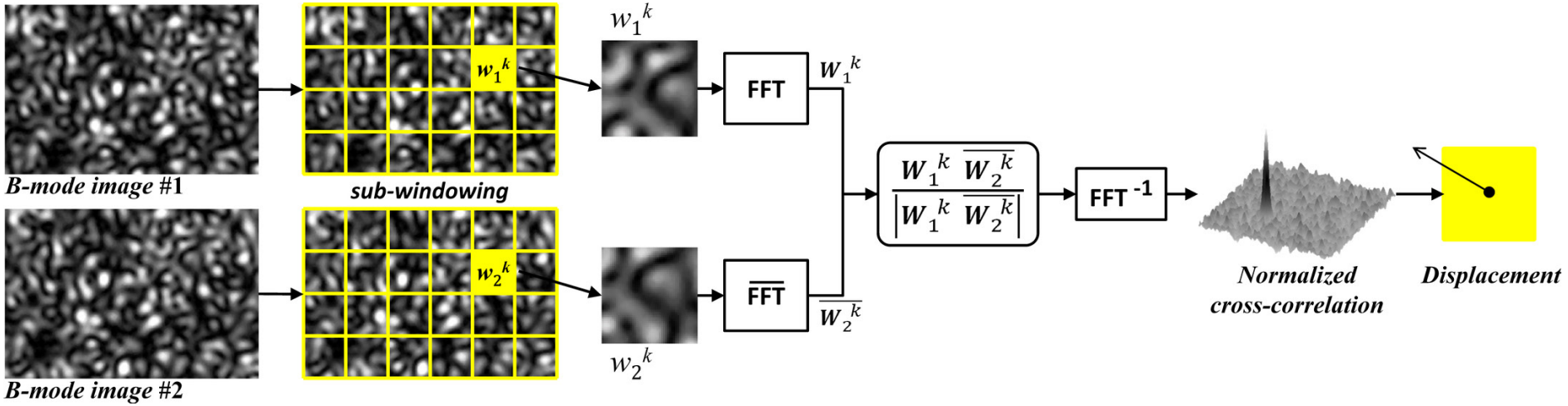
4. **Coarse-to-fine estimation** to detect both large and small displacements (goes in hand with #1)
5. **Regularization** to smooth the vector field

FFT-based X-correlation

Cross-correlation theorem

- multiplying the Fourier transform of one function by the complex conjugate of the Fourier transform of the other gives the Fourier transform of their correlation

$$f \star g = \mathcal{F}^{-1}(F \times \bar{G})$$



source: Garcia D *et al*. Introduction to speckle tracking in cardiac ultrasound imaging. Institution of Engineering and Technology. 2018

the different steps of the algorithm

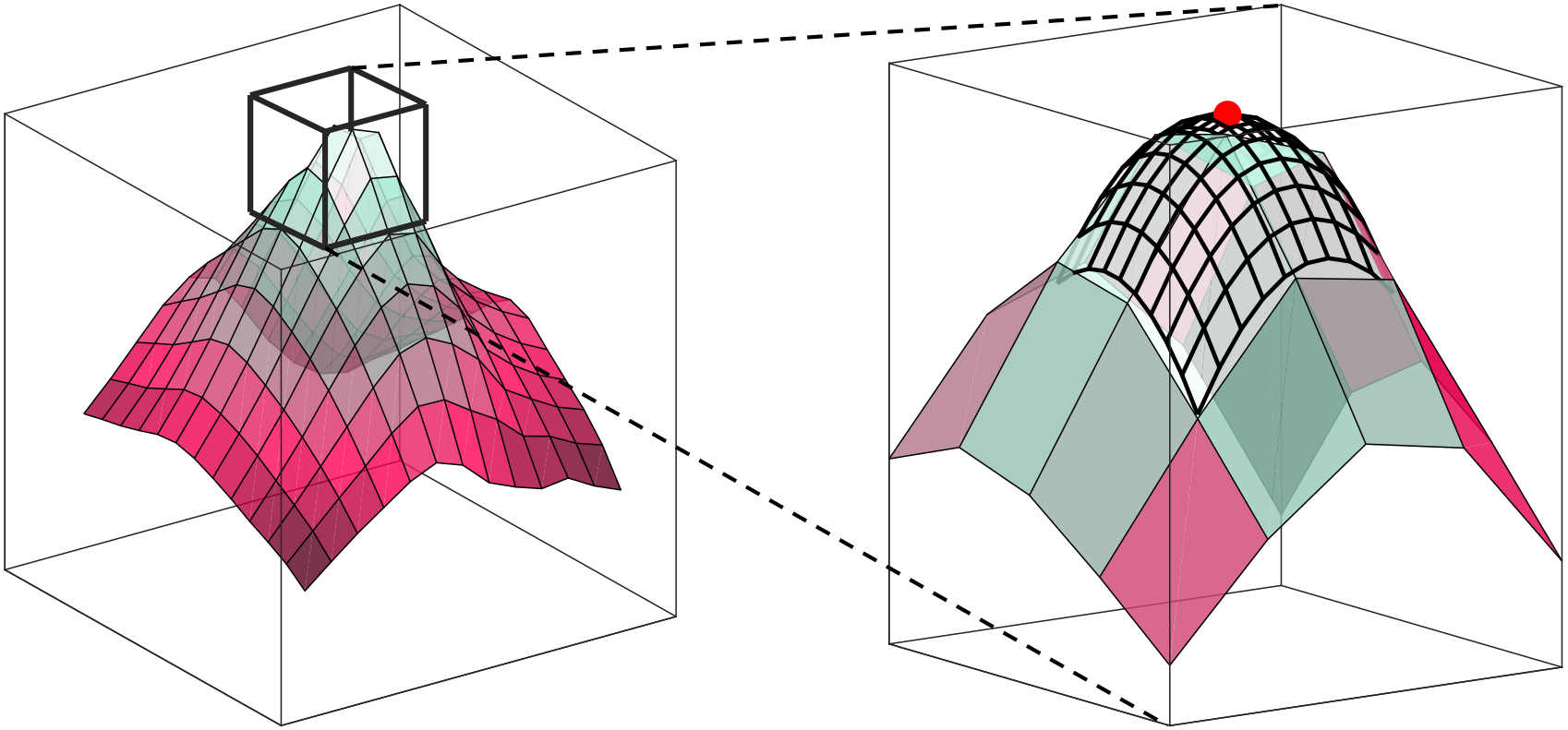
- the previous slide (*FFT-based X-correlation*) illustrates the core of the algorithm
- **additional steps are required to improve accuracy**

1. the displacements are not integer ⇒ **sub-pixel estimation** by **peak fitting**
2. displacements are small to large ⇒ **multi-scale coarse-to-fine** approach
3. the images are noisy ⇒ several successive images + **ensemble correlation**
4. the displacements are noisy ⇒ **robust smoothing**

❶

- **The cross-correlation is a pixelwise technique**
  (i.e. displacements are 0, 1, 2, 3… pixels)

- **A peak fitting yields subpixel displacements**

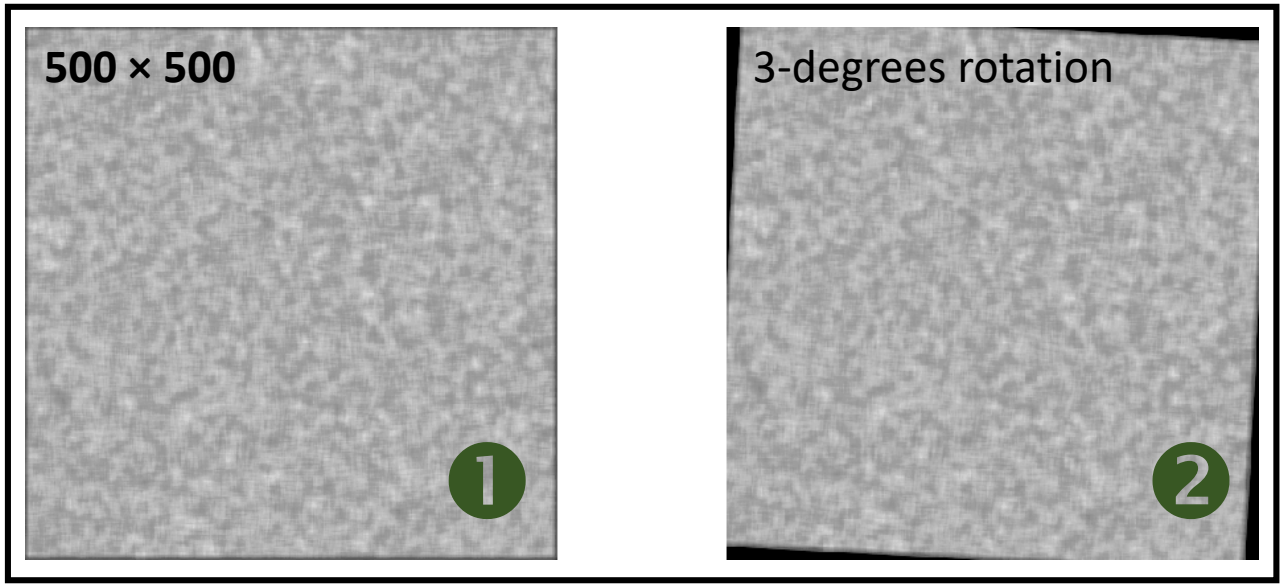


normalized cross-correlation

paraboloid-based peak fitting

multi-scale coarse-to-fine approach

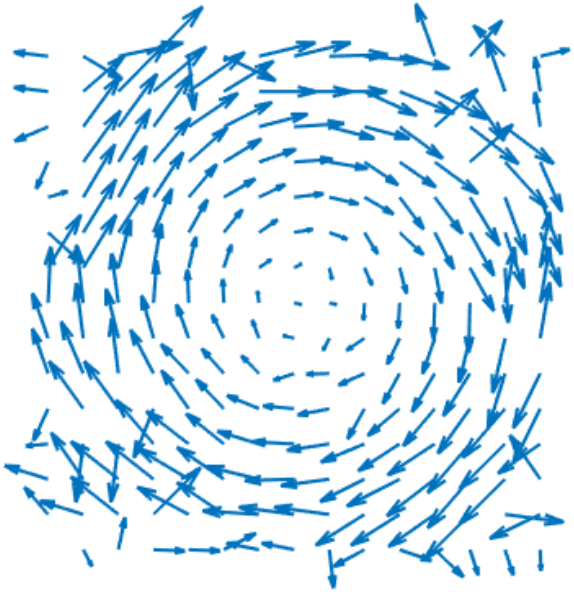
❷

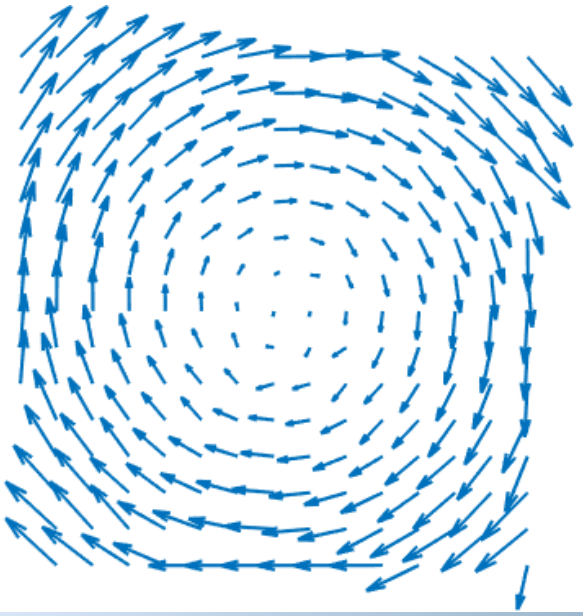


32 × 32

64 × 64 / 48 × 48 / 32 × 32

one-scale





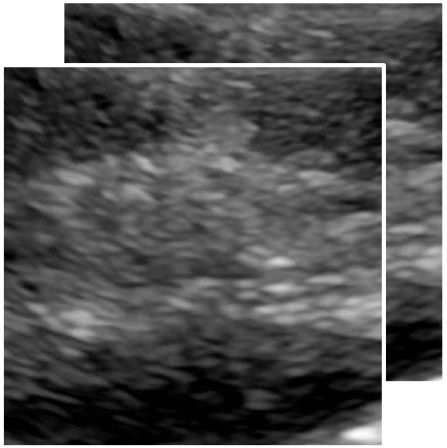
multi-scale

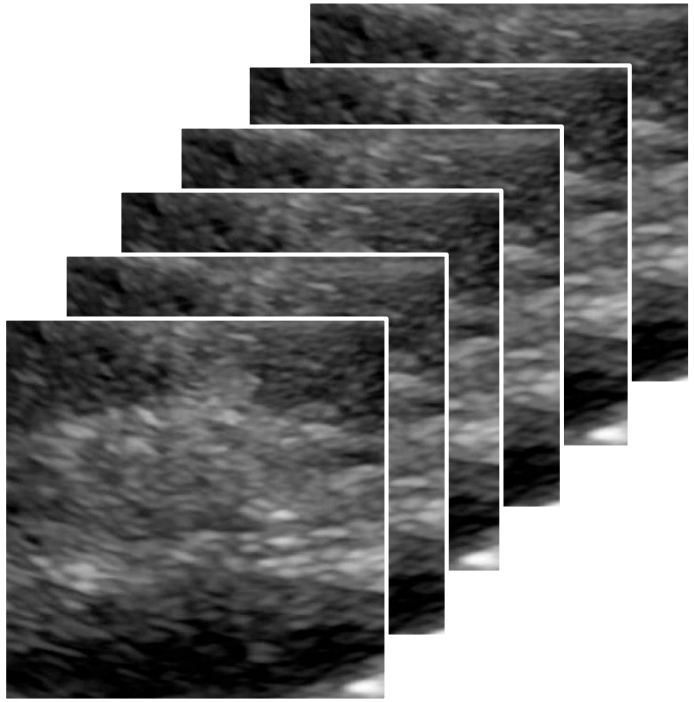
ensemble approach

❸

- We often have a series of successive images in ultrasound imaging
- And this is all the more true in ultrafast imaging…

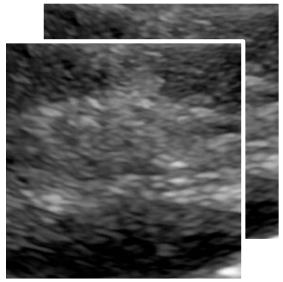
Recommendation: to improve accuracy, use **several pairs of images instead of one**

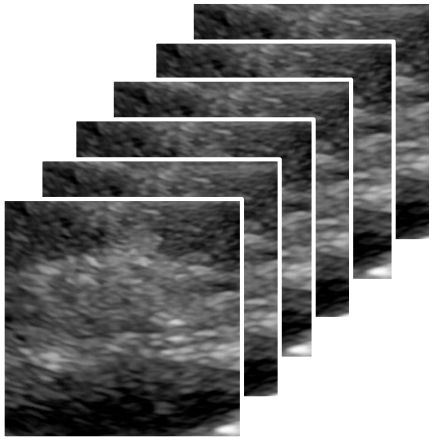




ensemble approach (cont'd)

❸





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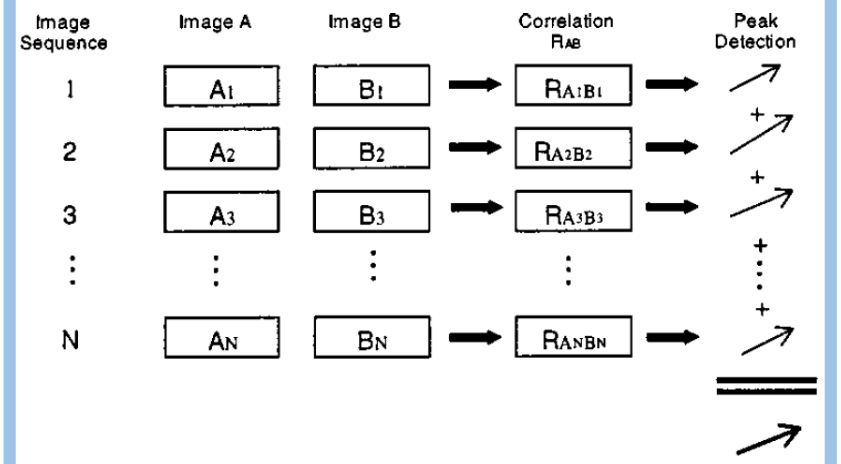
A PIV Algorithm for Estimating Time-Averaged Velocity Fields

Journal of Fluids Engineering
JUNE 2000, Vol. 122 / **285**

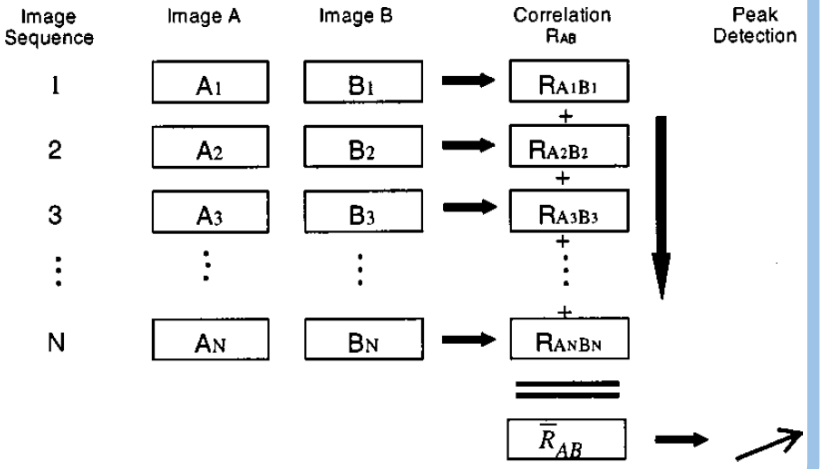
average velocity method
vs.
average correlation method

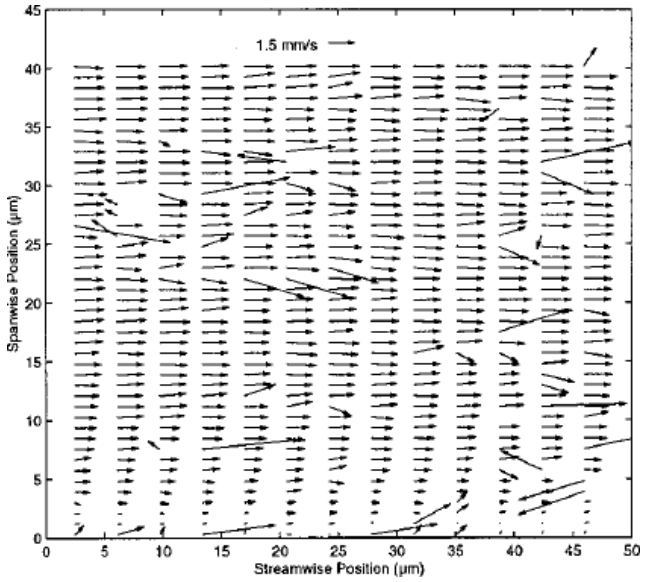
ensemble approach (cont'd)

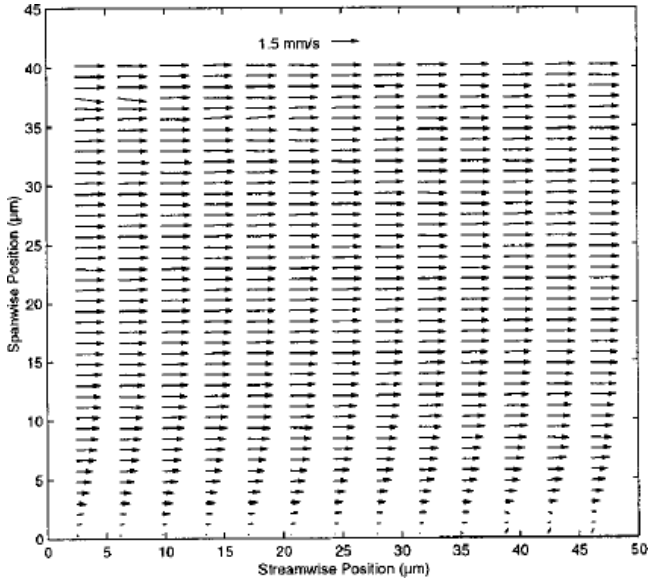
3 average velocity



average correlation

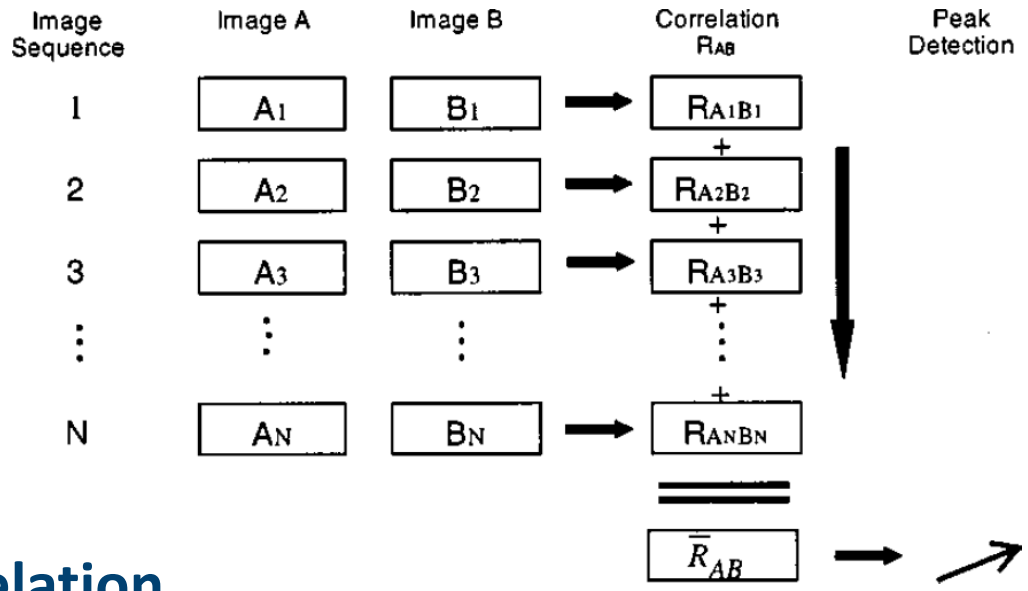




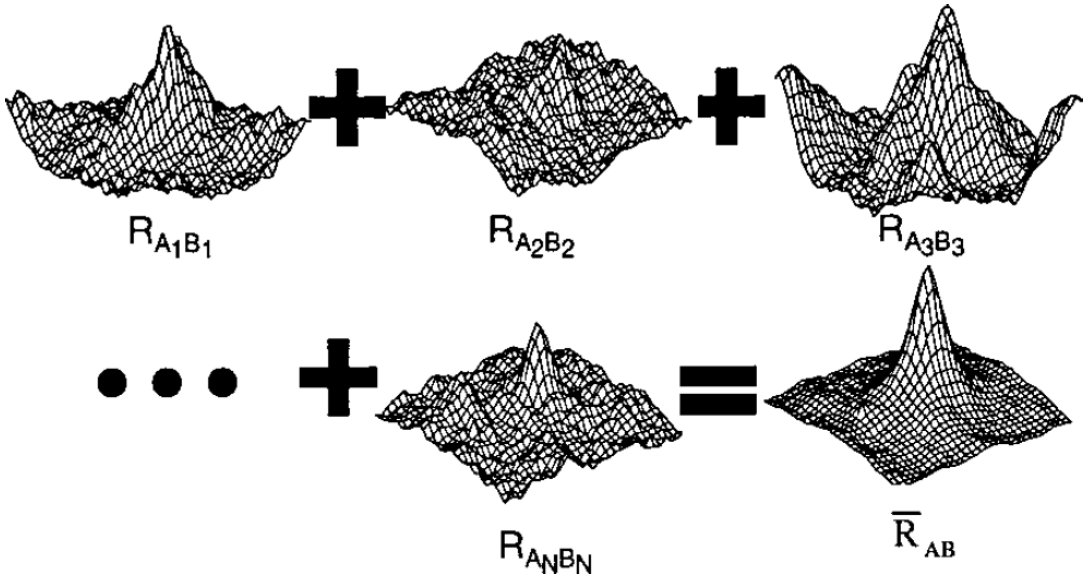


ensemble approach (cont'd): average correlation

❸



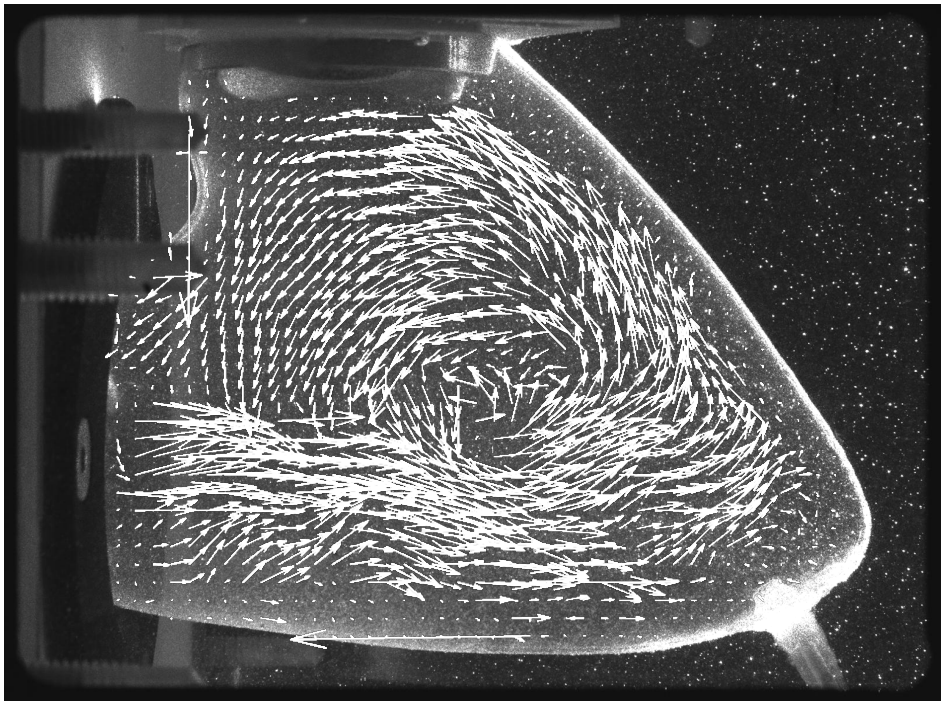
average correlation

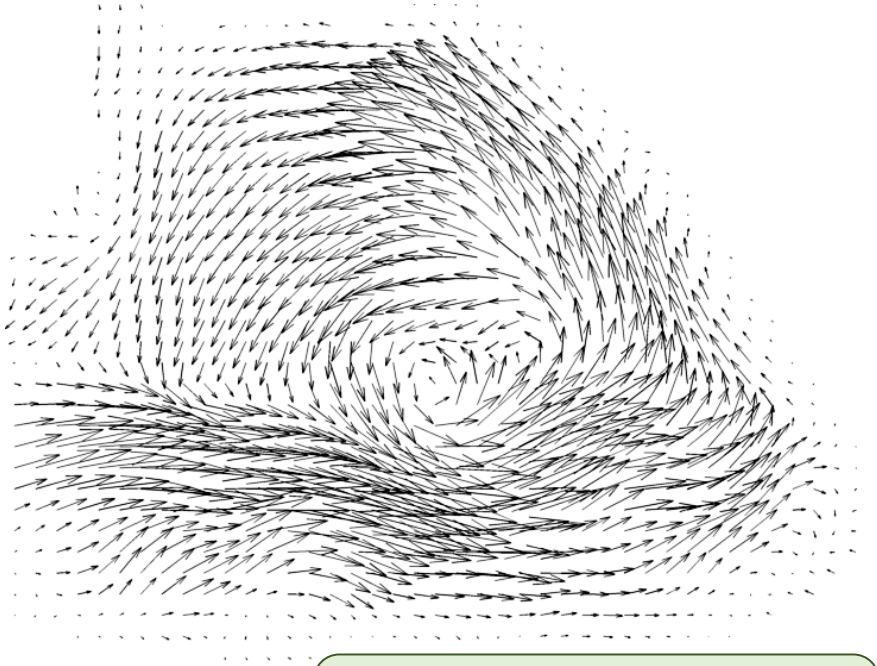


4

- The estimated displacement field is **noisy** and may contain **outliers**

Recommendation: use a **robust smoother**





key paper

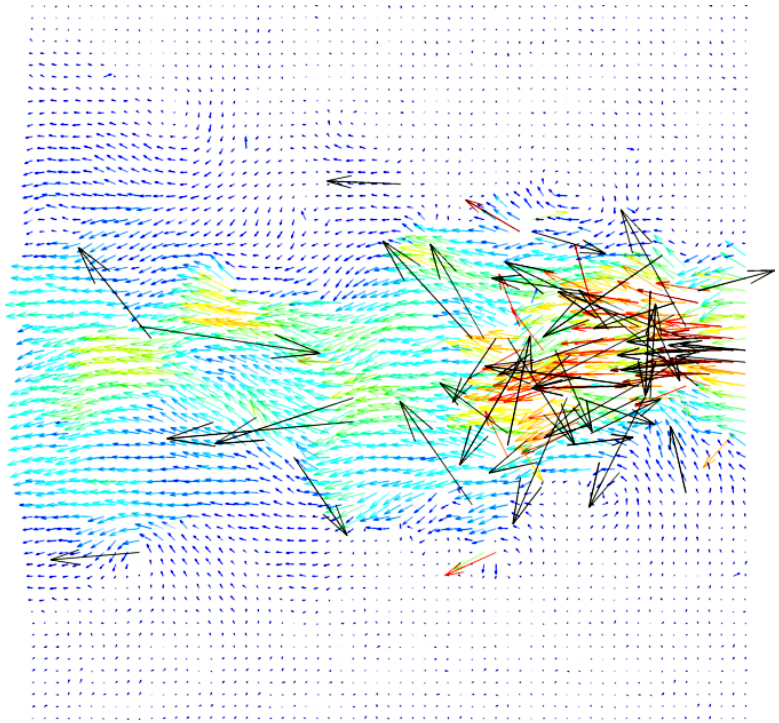
- Garcia. Exp in Fluids 2011;50:1247-1259

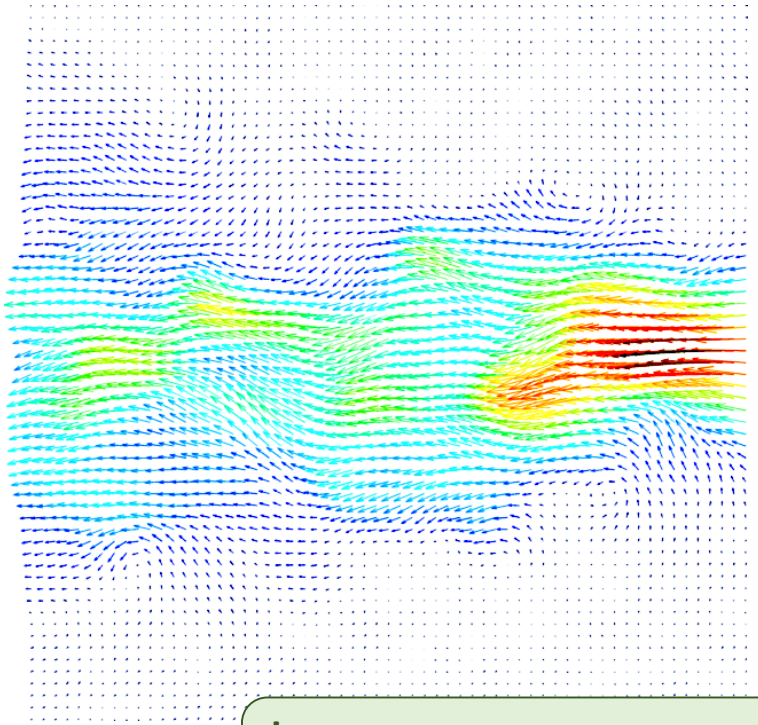
smoothing

4

- The estimated displacement field is **noisy** and may contain **outliers**

Recommendation: use a **robust smoother**





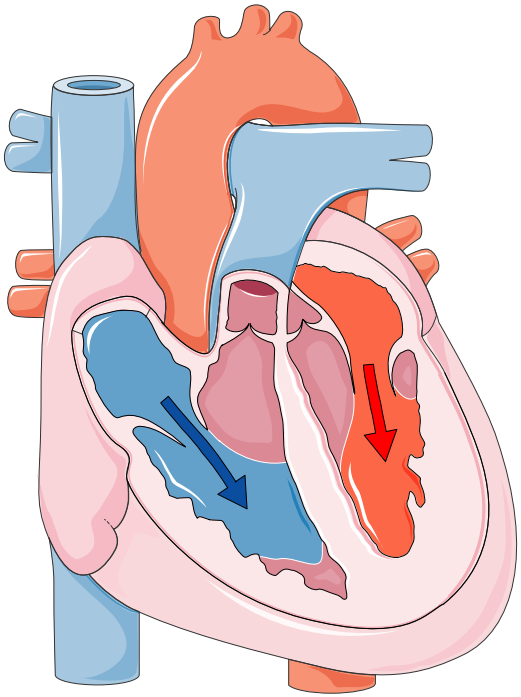
key paper

- Garcia. Exp in Fluids 2011;50:1247-1259

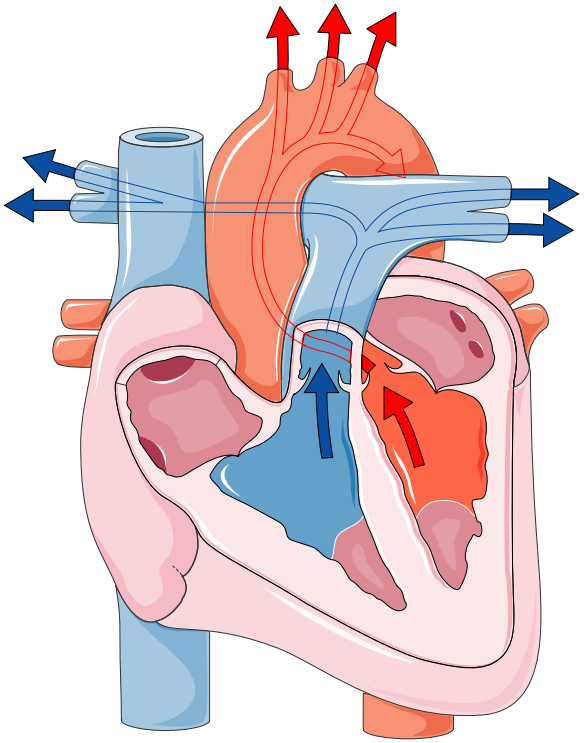
cardiac strain
IMAGING

systole & diastole

diastole = left ventricular filling



systole = ejection



Heart failure:
the pumping action is not strong enough to maintain a proper blood flow

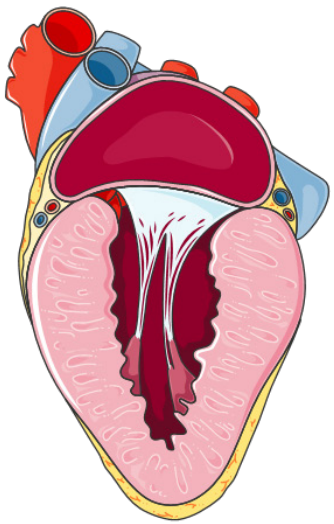


> 25 million worldwide

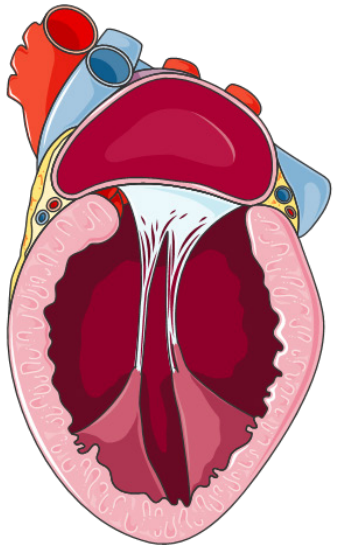


Hypertension





myocardial infarction

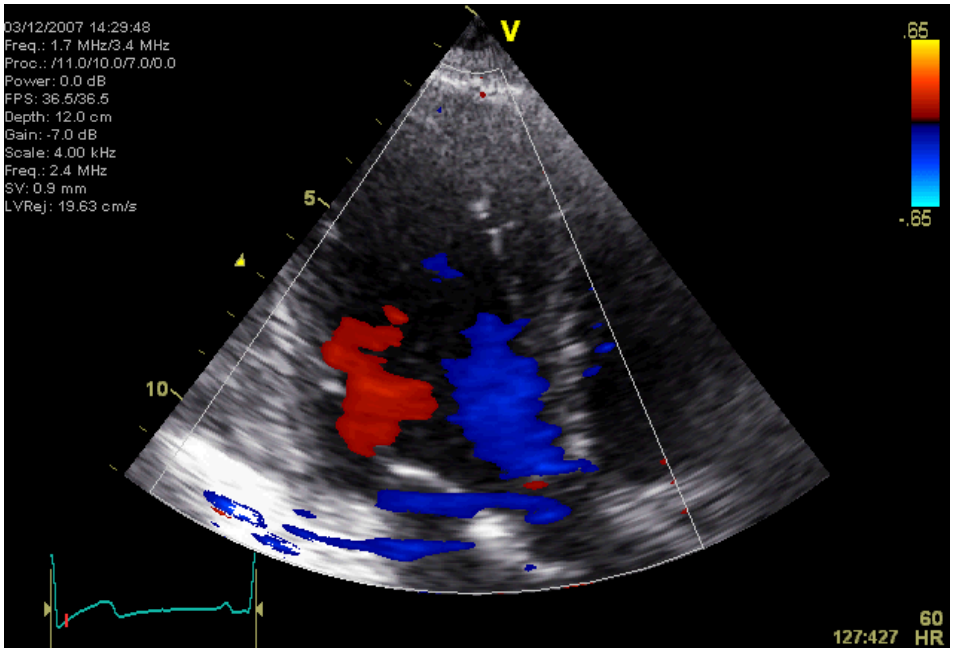


Diastolic heart failure
(preserved EF)

Systolic heart failure
(reduced EF)

transthoracic echocardiography







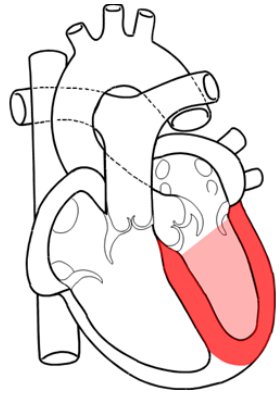
ultrasound-based biomarkers

Continuum of hypertensive cardiopathy

Morphological markers

- Dimensions
- Volumes
- Masses

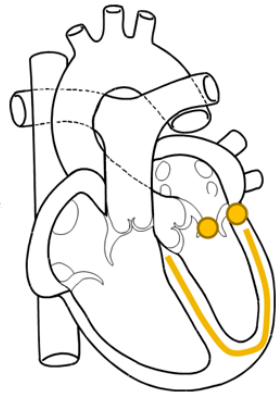
ROUTINE



Motion-based markers

- Mitral flow velocity
- Mitral annulus velocity
- **Global longitudinal strain (GLS)**

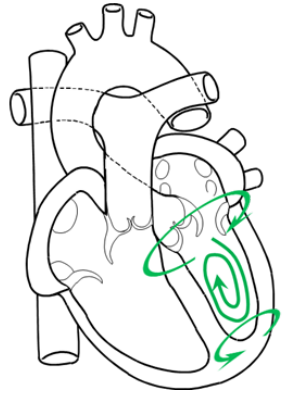
RECOMMENDED



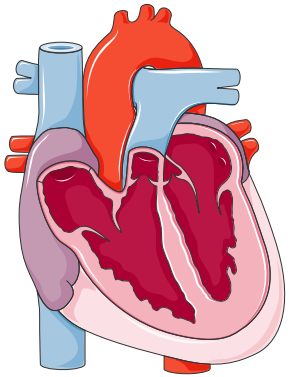
Early markers (??)

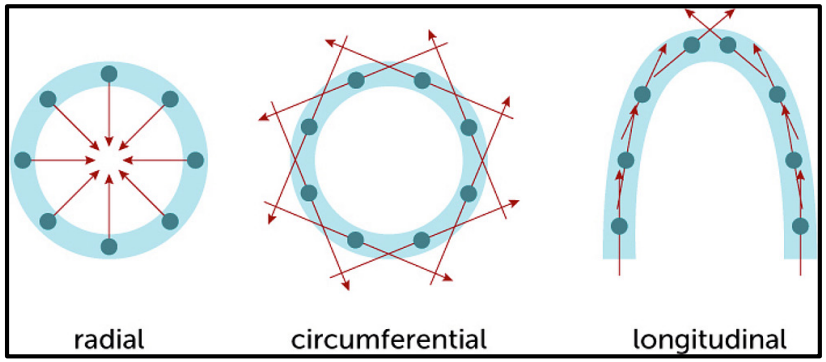
- Ventricular torsion
- Intraventricular pressure difference
- Intraventricular vortex

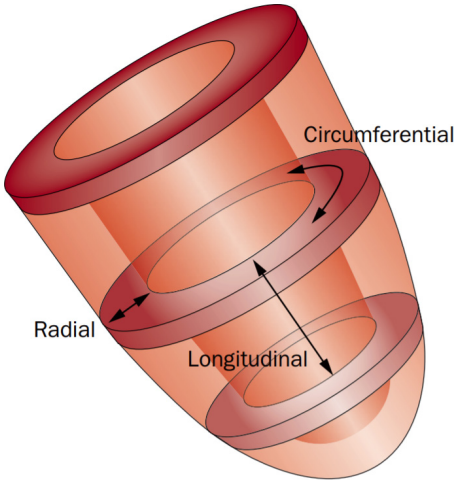
under investigation



myocardial strain imaging by speckle tracking



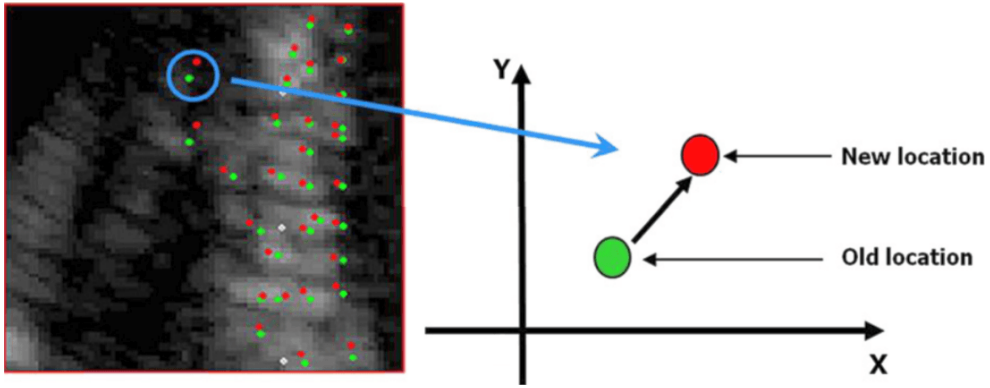




<u>Engineering strain</u> = ratio of total deformation to the initial dimension

$= \Delta L/L = (l - L)/L$

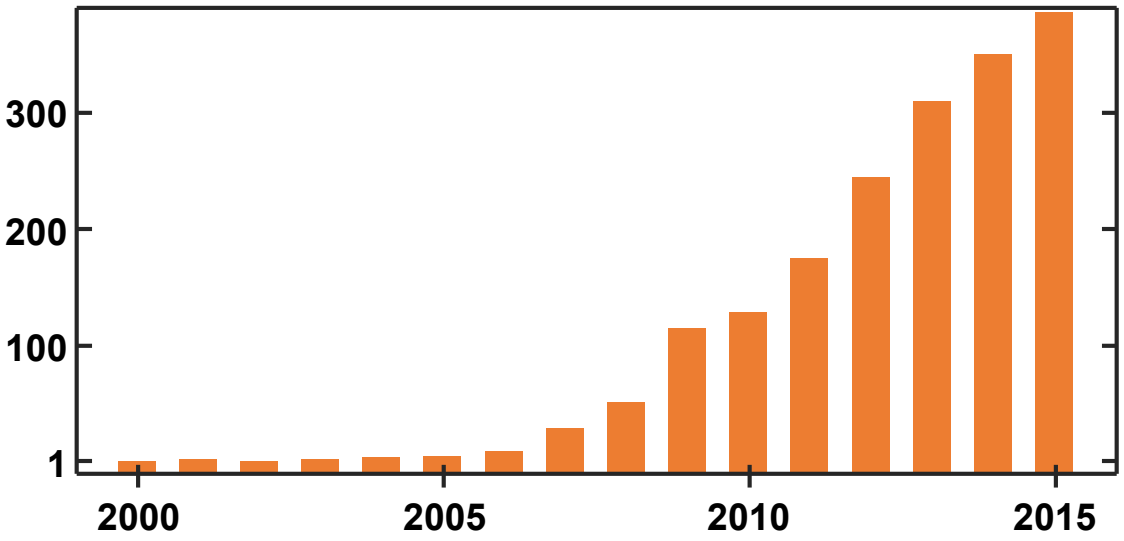
The most used approaches for myocardial strain imaging is <u>block-matching</u>.

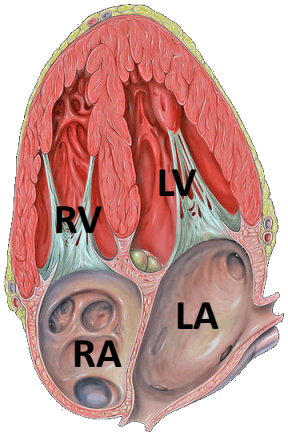


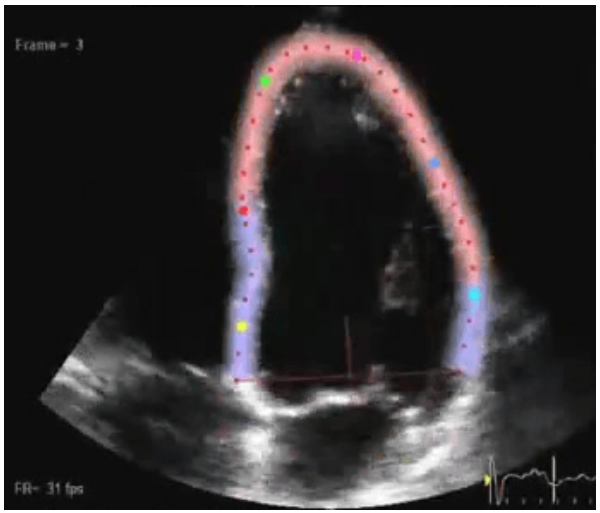
key paper

- Blessberger and Binder. Heart 2010;96:716-722

strain imaging by speckle tracking







book chapter

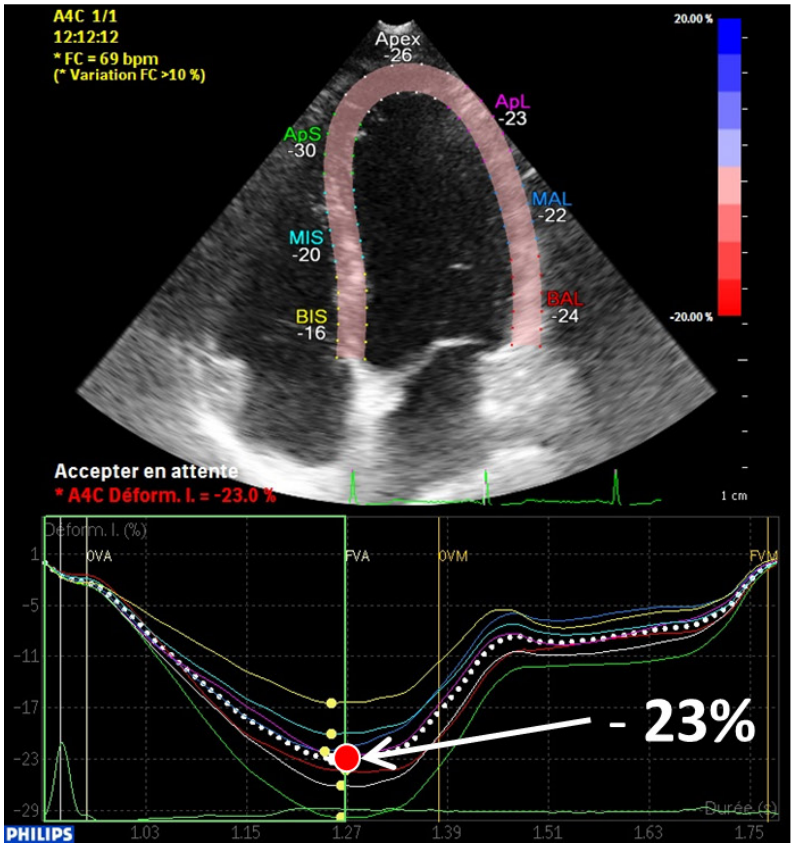
- Garcia *et al*. IET doi:10.1049/pbhe013e_ch26

GLS

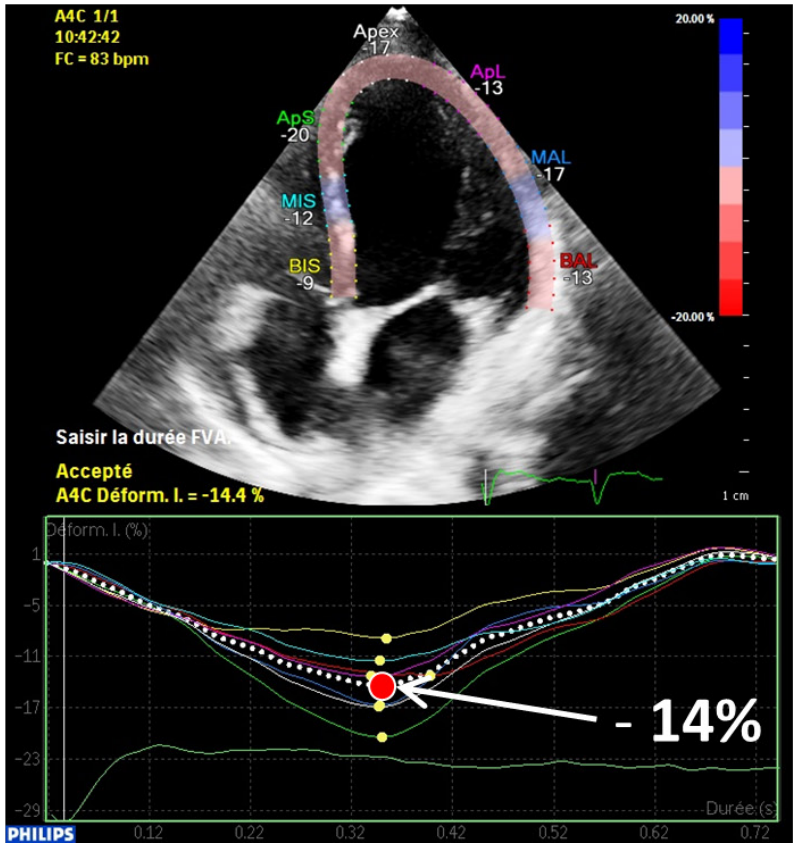
The peak GLS ("*Global Longitudinal Strain*") is a marker of the global systolic (ejection) function, complementary to ejection fraction

$\mathrm{GLS} = (l(t) - L_{ED})/L_{ED}$, with $l(t)$ the longitudinal myocardial length at t, and L_{ED} the length at end-diastole

Normal subject



Post chemotherapy



- Despite the thousands of articles published, local cardiac strain imaging is not recommended due to its poor inter-vendor reproducibility:

    1. different sequences / images
    2. different algorithms
    3. different smoothing techniques

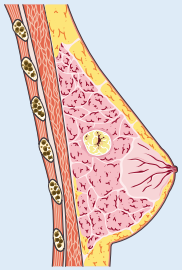
- Peak GLS is the only strain parameter which is now included in the echocardiography guidelines

- Peak GLS can improve diagnosis in

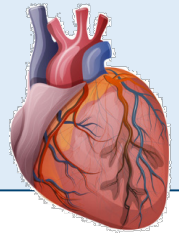
    1. Aortic stenosis



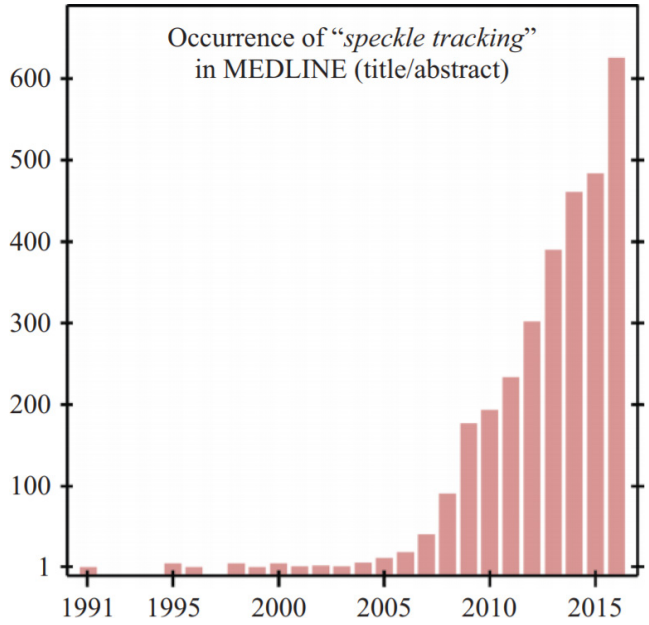
    2. Cardiotoxicity due to anti-cancer drugs



    3. Myocardial infarction



Strain imaging story: thousands of papers, M$ of research…



BUT…

Global longitudinal strain (GLS) is the most robust deformation parameter and is presently the only myocardial strain parameter which may be safely used in routine clinical practice

Farsalinos KE, Daraban AM, Ünlü S, Thomas JD, Badano LP, Voigt J-U. Head-to-head comparison of global longitudinal strain measurements among nine different vendors: the EACVI/ASE inter-vendor comparison study. J Am Soc Echocardiogr. 2015;28(10): 1171–1181