Physical simulation for deep learning

– Applications to motion estimation and image formation –

by

Olivier Bernard

Professor – University of Lyon (INSA), France

In collaboration with **Damien Garcia** (INSERM, CREATIS, France)

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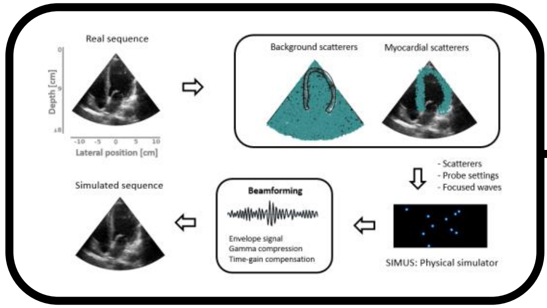
CREATIS; CNRS (UMR 5220); INSERM (U1294); INSA Lyon; Université de Lyon, France

Successful AI solutions trained on simulated images exclusively



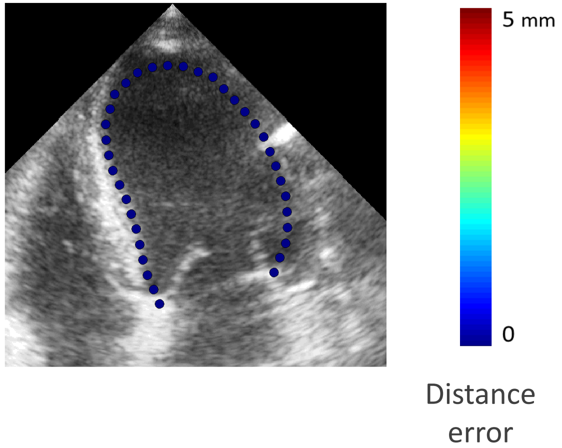
Simulation pipeline

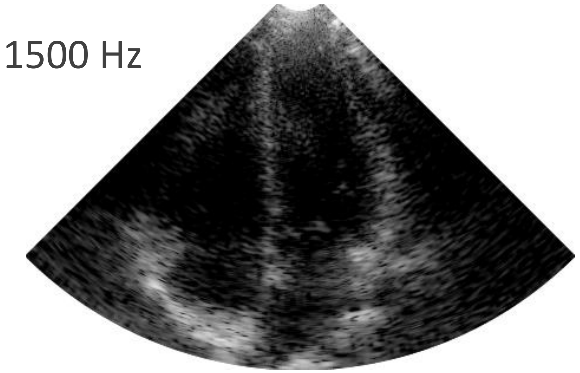
AI solutions

Tissue motion estimation

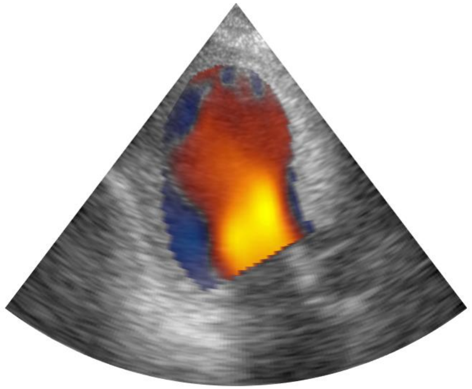
Ultrafast cardiac imaging

Color Doppler imaging





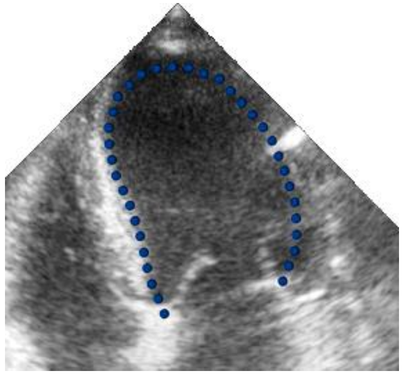
[Lu et al., IEEE IUS 2023]



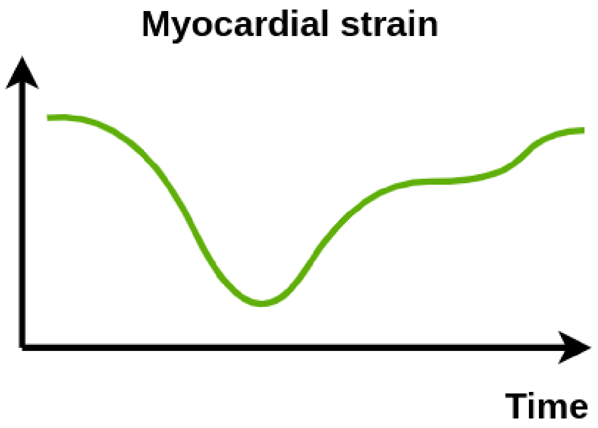
[Puig et al., IEEE IUS 2023]

Quantification of clinical indices to diagnose cardiac pathologies

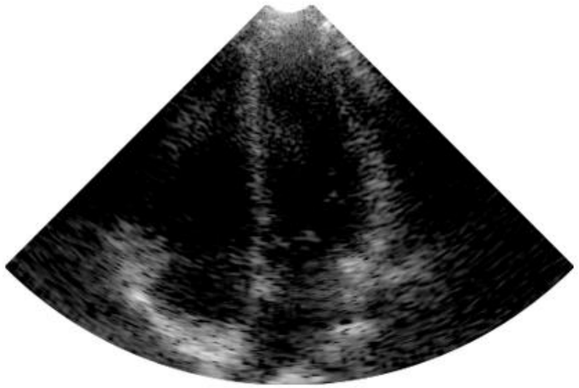
Conventional imaging



Tracking of tissue structures



Ultrafast imaging



Extraction of mechanical properties

- Myocardial stiffness
- Myocardial elasticity
- Others…

Echocardiographic imaging

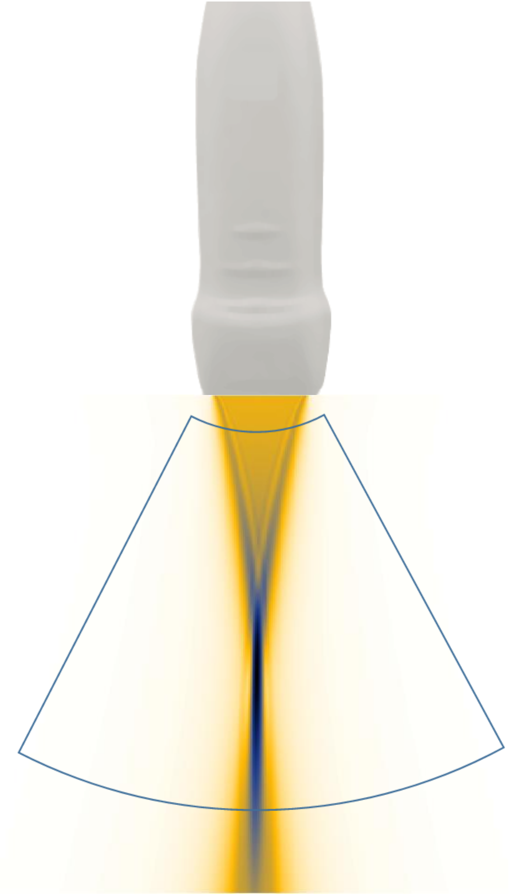
Challenges

- How to make the motion estimation from images more accurate and reproducible ?
- Is it possible to significantly increase frame rate while maintaining image quality ?

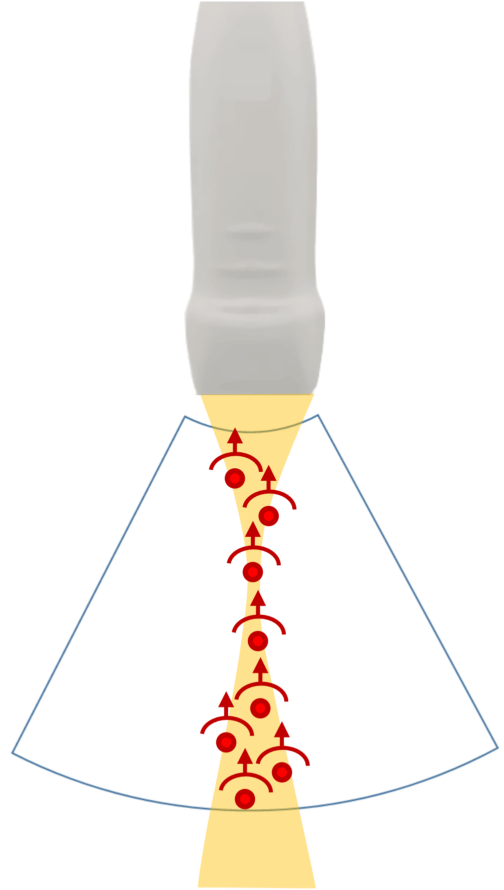
Principle of image formation in echocardiography

Generating images from sounds

Transmission of a focused US wave

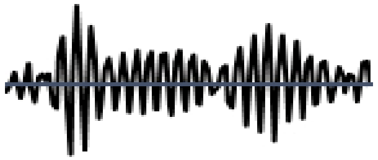


Reflected waves are received by the transducer



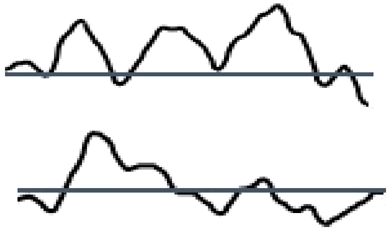
Beamforming

RF signal (real)

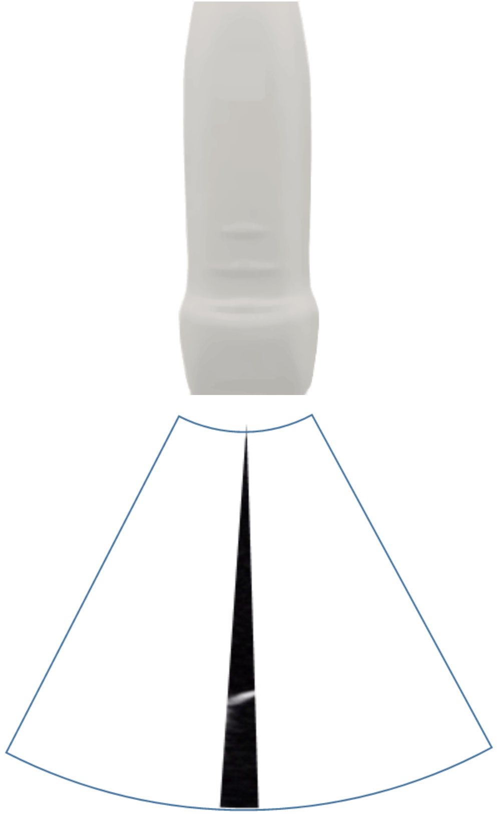


Demodulation

IQ signal (complex)

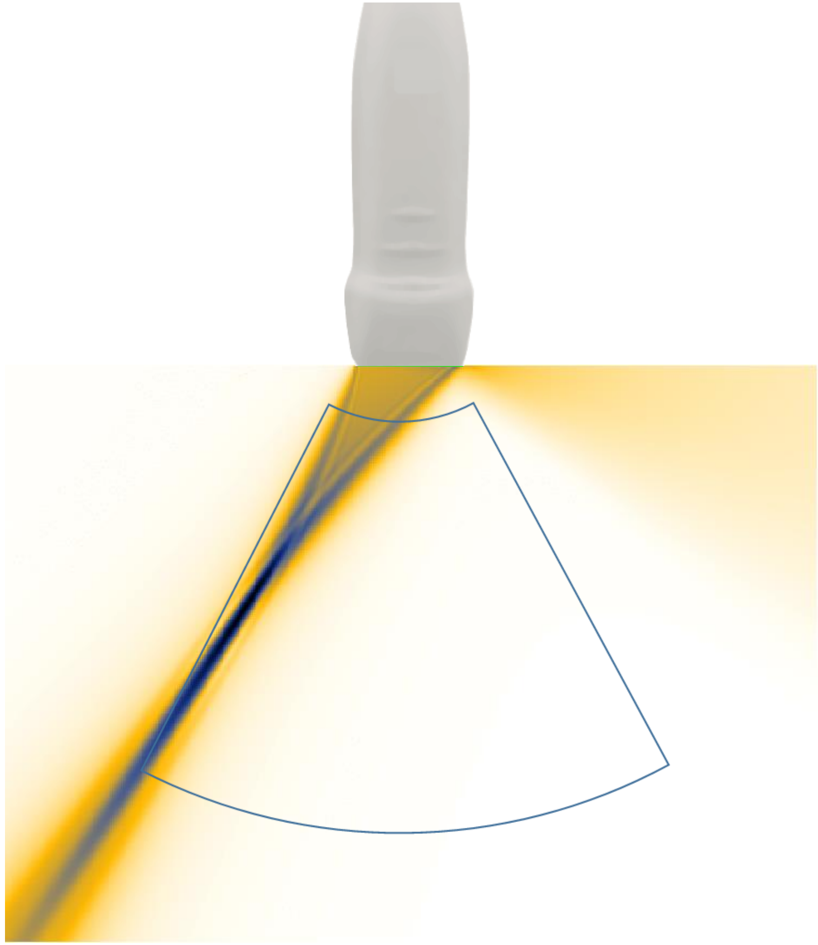


Envelope signal
Gamma compression
Time-gain compensation



Focus-wave transmit

Conventional imaging technique



PRF = 4500 Hz

Depth <= 17 cm

90 firings for 1 image

Frame rate = 50 Hz

Diverging-wave transmit

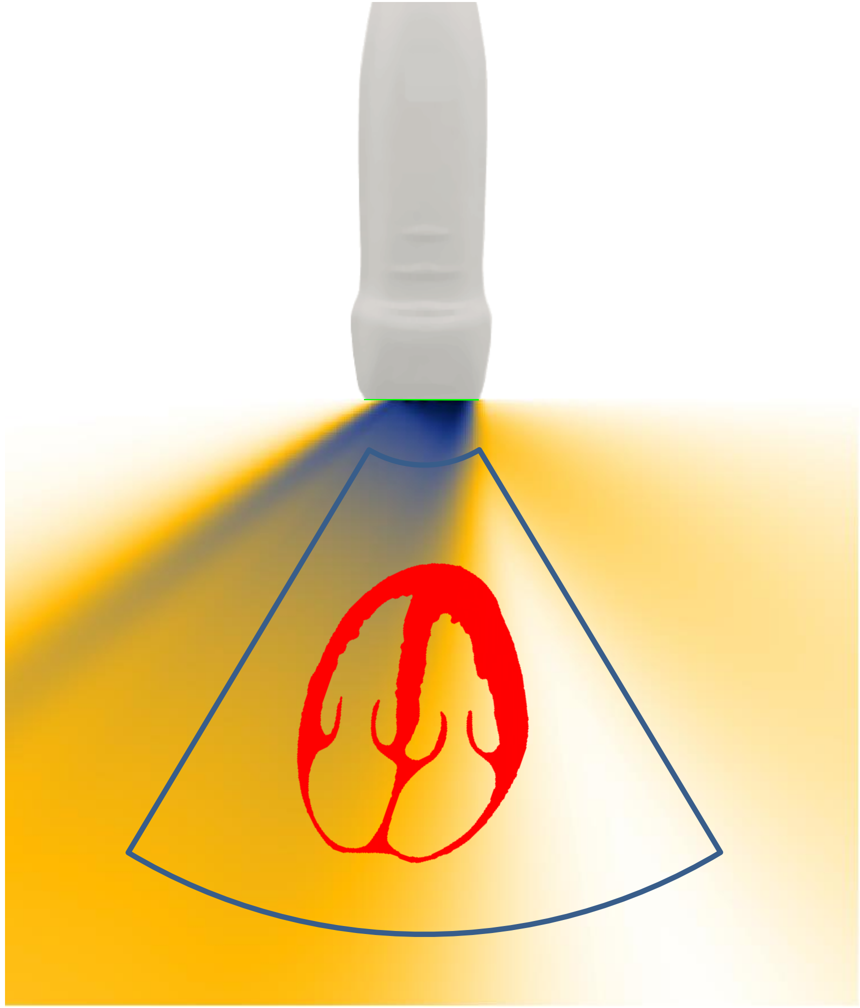
Fast imaging technique

PRF = 4500 Hz

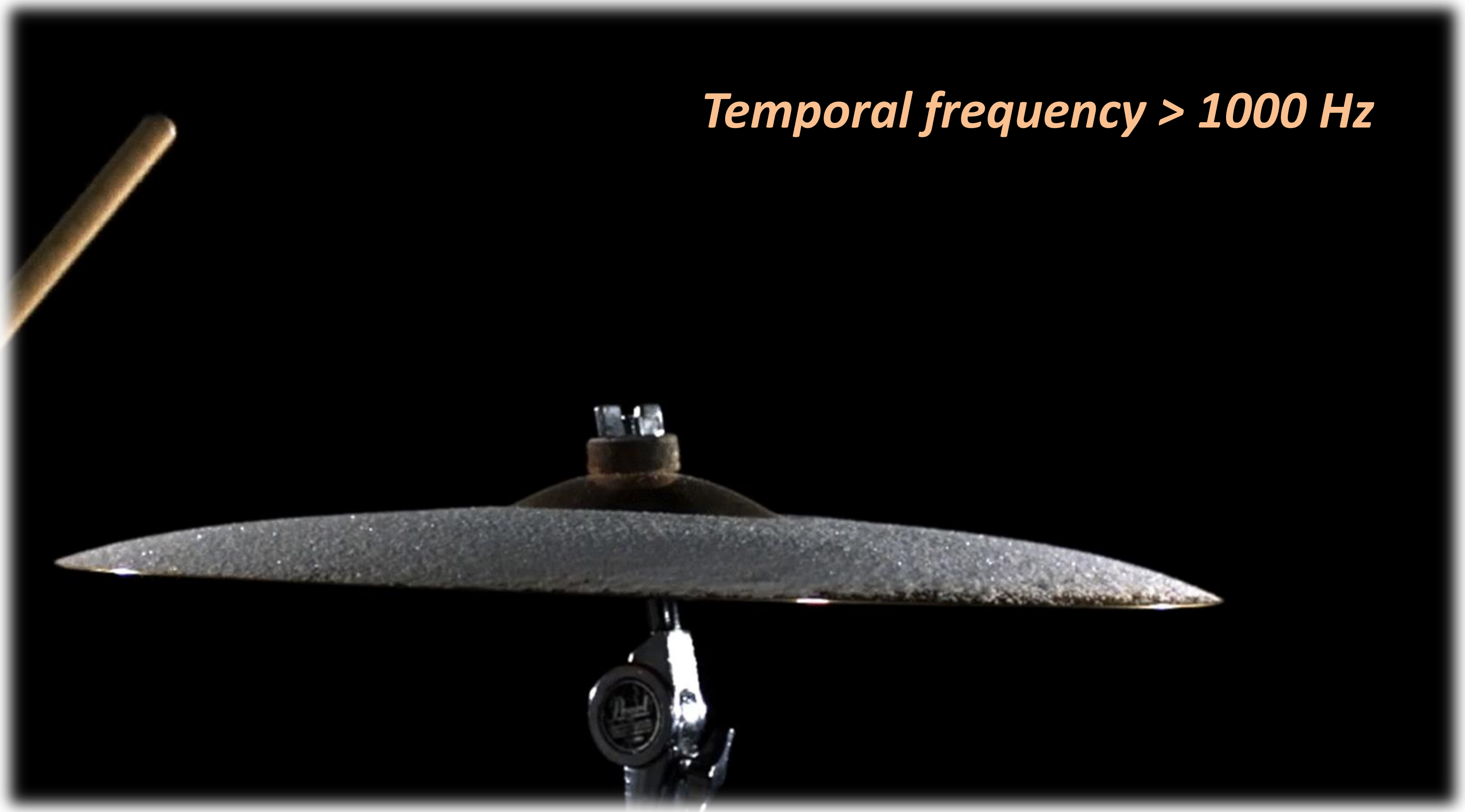
Depth <= 17 cm

31 firings for 1 image

Frame rate = 145 Hz



Potential for ultrafast imaging



Generation of realistic synthetic echocardiographic sequences

[Alessandrini et al., IEEE TMI 2016]

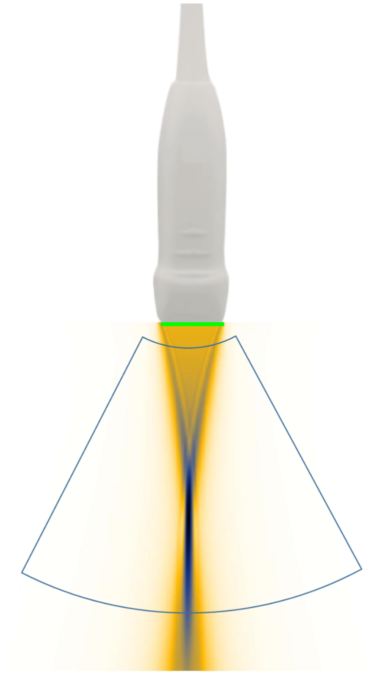
[Evain et al., IEEE TMI 2022]

[Sun et al., IEEE TUFFC 2022]

[Lu et al., IEEE IUS 2023]

Target applications

Transmission scheme

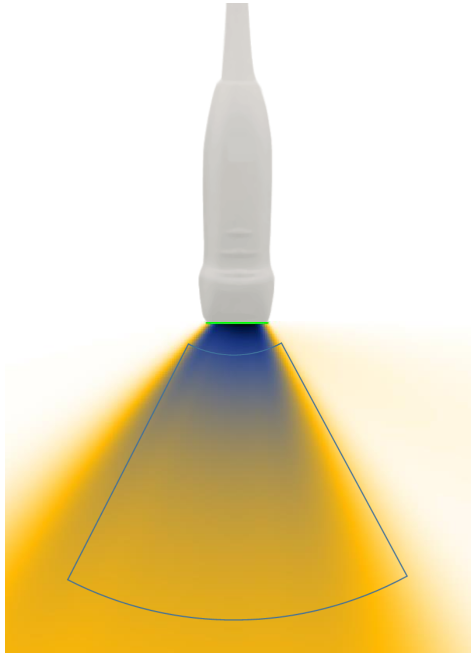


Classical scheme

(Focused waves)

Ultrafast scheme

(Diverging waves)



Deep learning for motion estimation

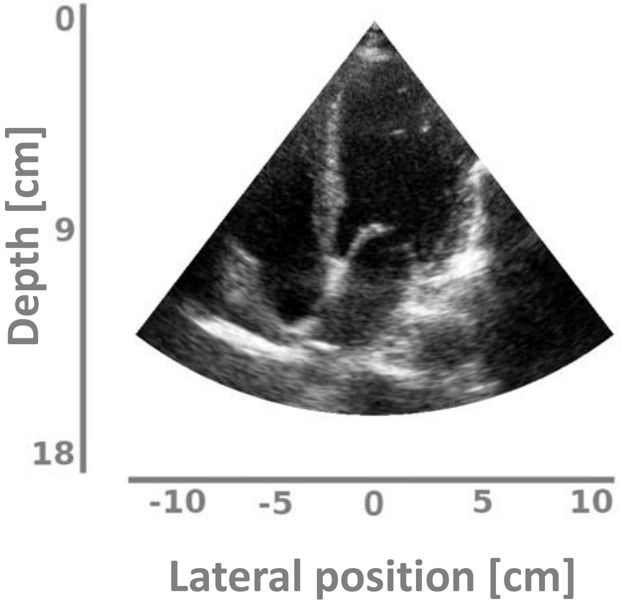
Frame rate: 50 Hz

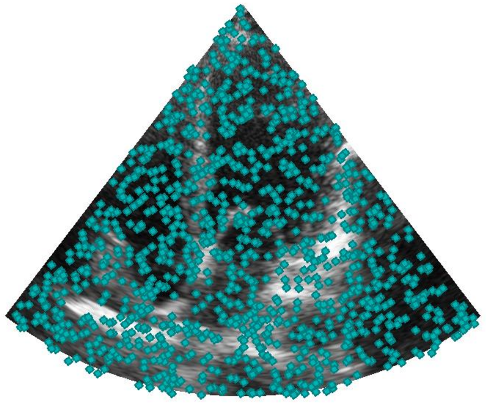
Deep learning for ultrafast cardiac imaging

Frame rate: 1500 Hz

Single-frame B-mode simulation workflow

Real sequence





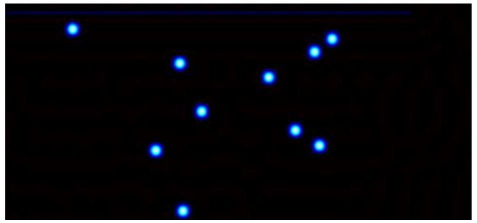
10 scatterers per resolution cell (λ^2)

$$RC_m = (I_m/255)^{(1/\gamma)} \cdot \mathcal{N}(0,\, 1)$$

Scatterers & probe settings

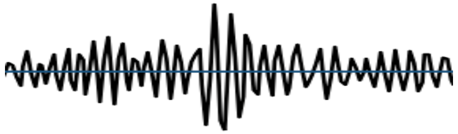
64 elem. phased array
2.6 MHz center freq.
Transmission scheme

SIMUS: Physical simulator



[Garcia et al., CMPB 2022]

Beamforming



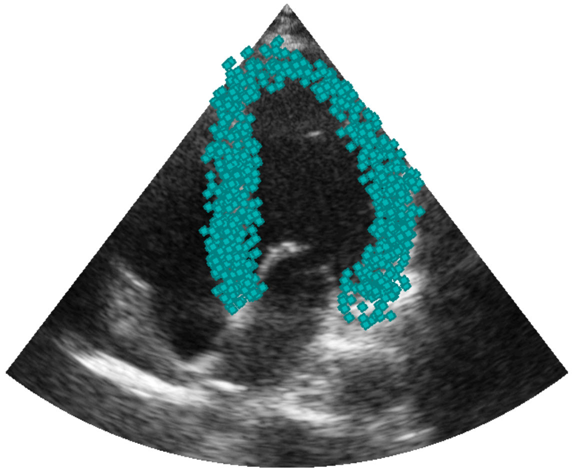
Envelope signal
Gamma compression
Time-gain compensation

Simulated sequence

Scatterers strategy

Spatial density

- ✓ 10 scatterers per λ^2

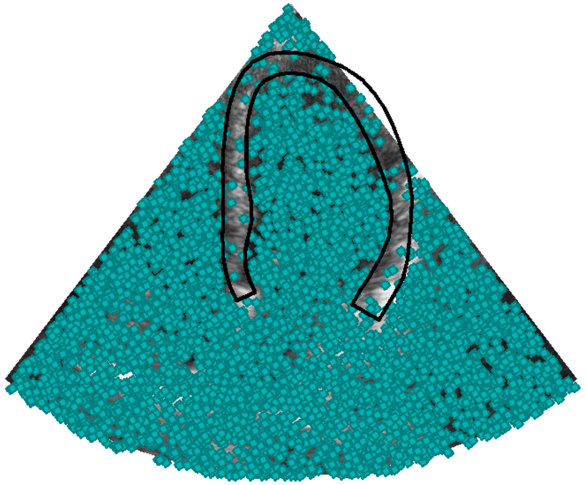


Myocardium

- ✓ Position updates from a dedicated strategy
- ✓ Reflection coefficients remain unchanged

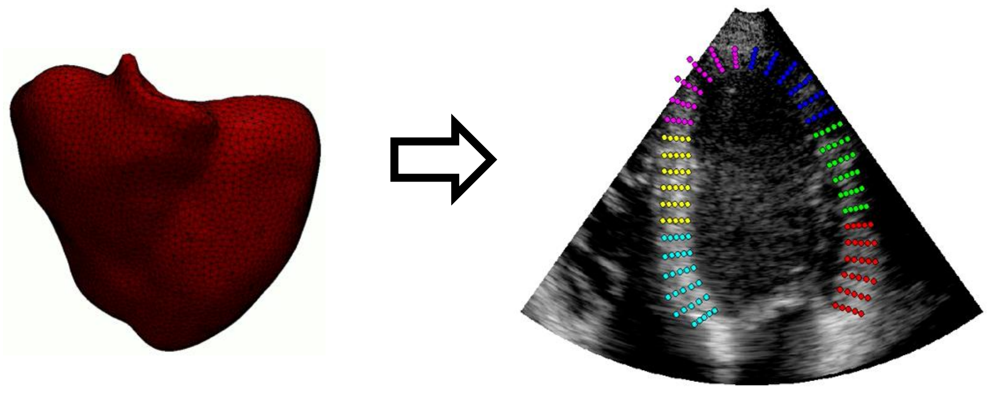
Background

- ✓ Positions remain unchanged
- ✓ Reflection coefficients updated directly from the real sequence



Myocardial scatterers strategy

Electromechanical model (@INRIA, France)

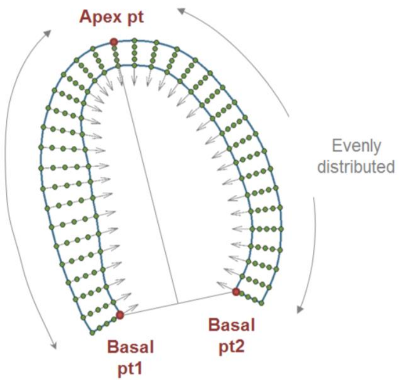


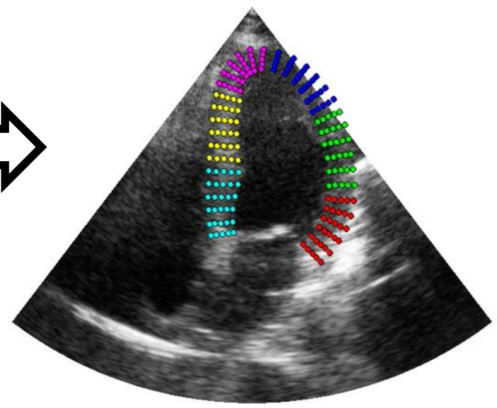
Validation of myocardial motion estimation

✓ SyntheticMultiVendors - open access dataset

[Alessandrini et al., IEEE TMI 2018]

Simple remeshing strategy





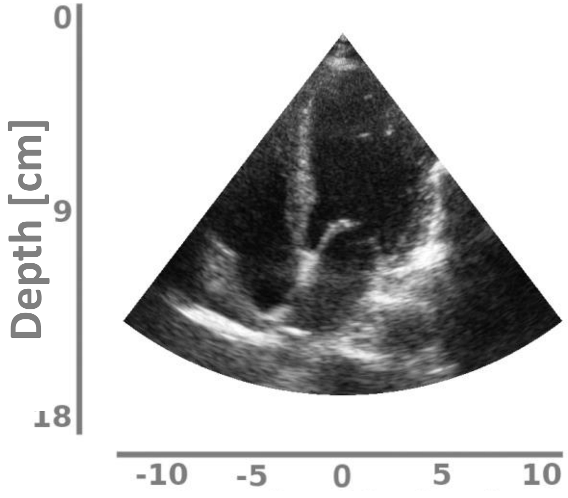
Myocardial motion estimation with deep learning

✓ SyntheticCAMUS - open access dataset

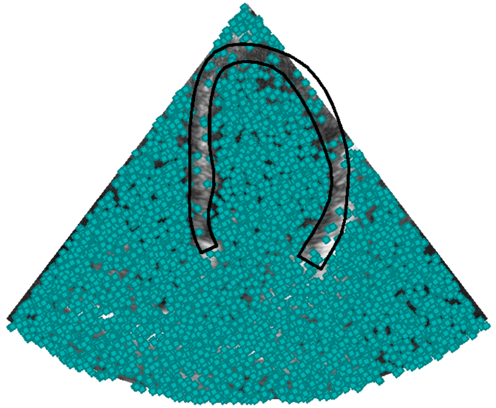
[Evain et al., IEEE TMI 2022]

B-mode sequence simulation workflow

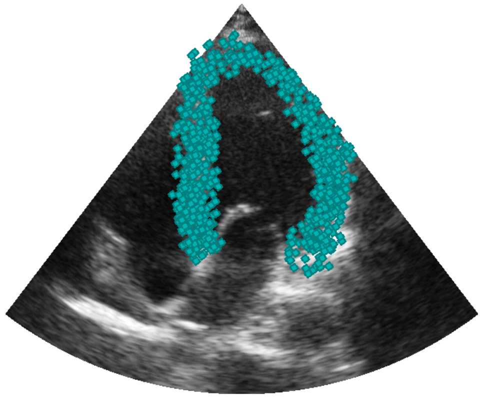
Real sequence



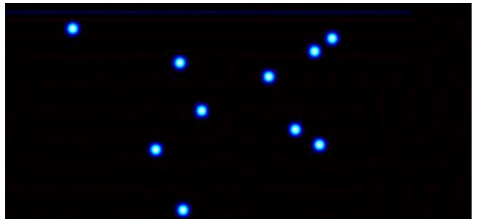
Background scatterers



Myocardial scatterers

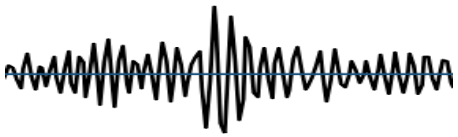


- Scatterers
- Probe settings
- Focused waves



SIMUS: Physical simulator

Beamforming



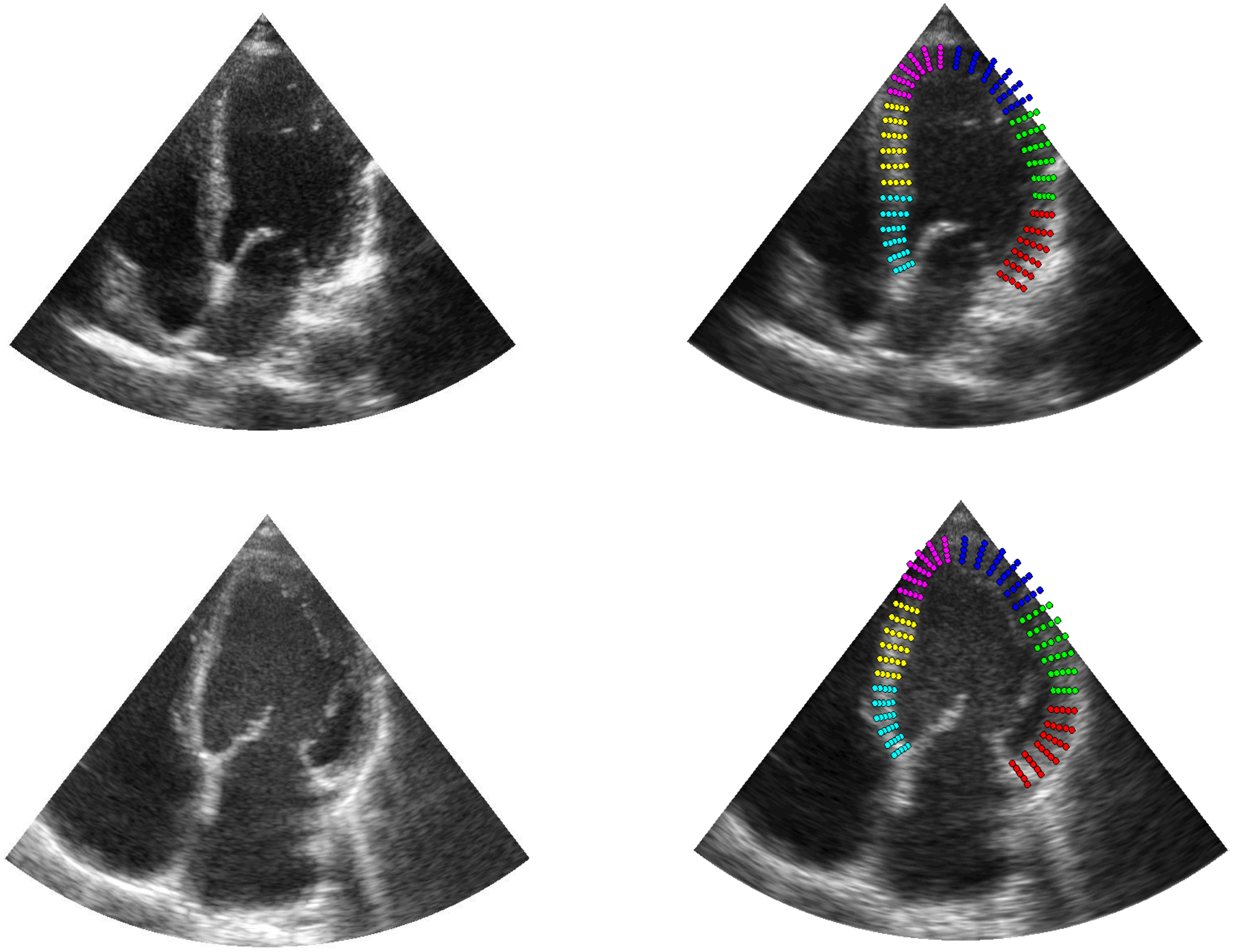
Envelope signal
Gamma compression
Time-gain compensation

Simulated sequence

SyntheticCAMUS dataset - properties

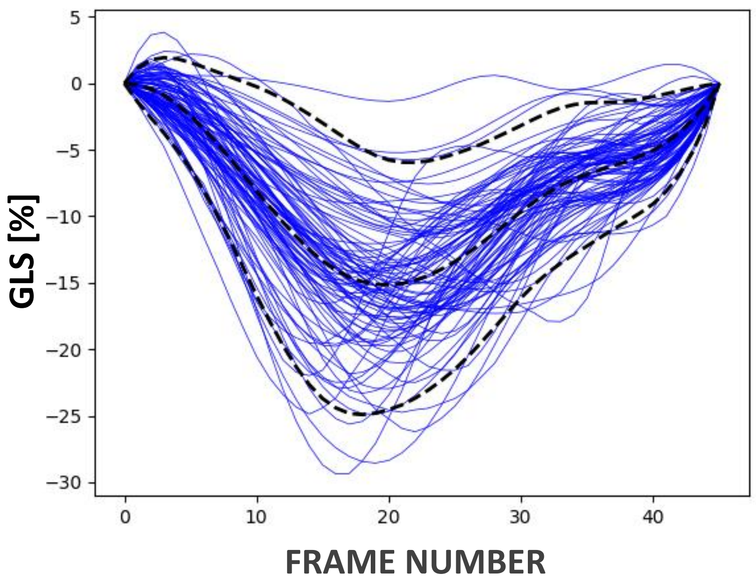
Real B-mode sequences

Simulated B-mode sequences with meshes



High variability/richness for AI methods

Global Long Strain (GLS)

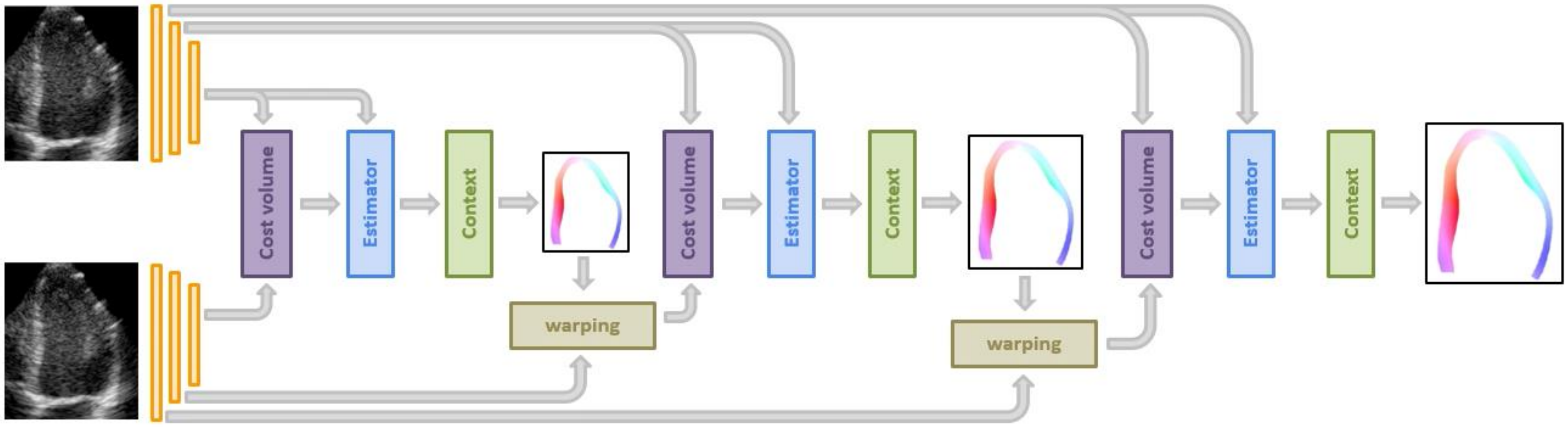


Tissue motion estimation in echocardiography with deep learning

[Evain et al., IEEE TMI 2022]

Numerous DL methods for motion estimation

- ✓ PWCNet, RAFT, FlowFormer, …



cPWC-Net architecture dedicated to motion estimation

Evaluation strategy

Motion estimation error

- ✓ EPE: End point Error (mm)

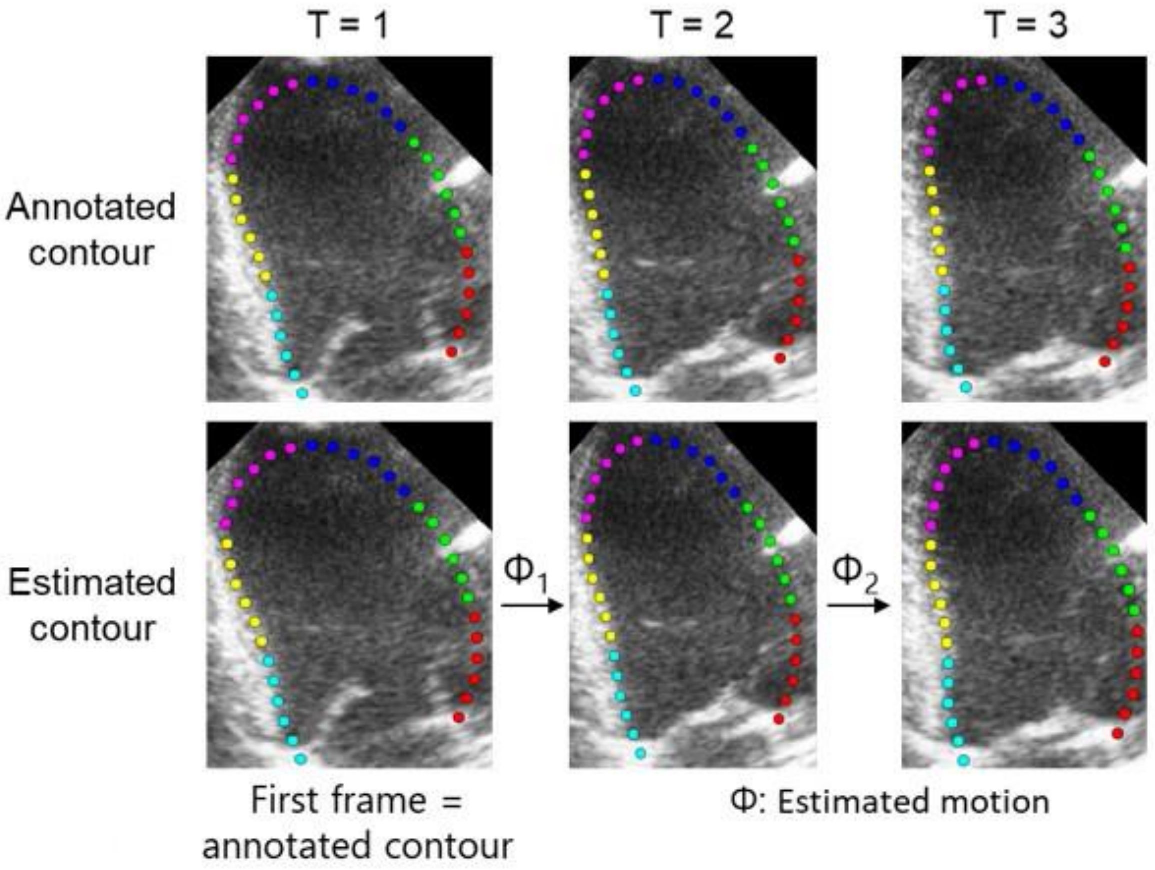
Geometric metrics

- ✓ d_m: Average distance (mm)
- ✓ d_H: Hausdorff distance (mm)

Clinical metrics

Estimated from tracked contours

- ✓ GLS (%)



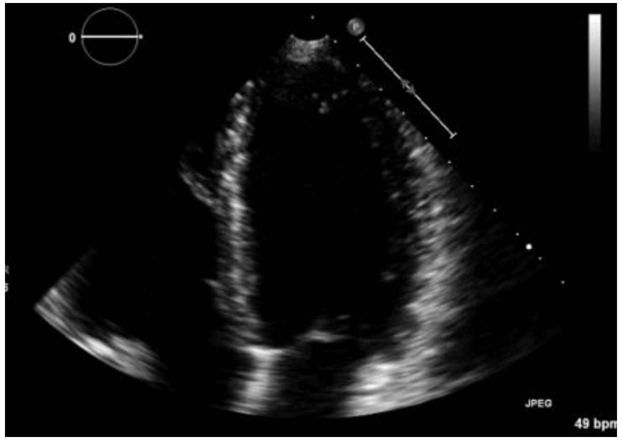
Evaluation of method generalization

First dataset

- ✓ From GE scanners
- ✓ From the open access dataset CAMUS
- ✓ University hospital of St Etienne, France
- ✓ Testing dataset: 30 patients in A4C
  1443 annotated image pairs

Second dataset

- ✓ From Philips scanners
- ✓ Private dataset
- ✓ University hospital of Caen, France
- ✓ Testing dataset: 30 patients in A4C
  1536 annotated image pairs
  5 groups of pathologies



Tested methods

PIV

- ✓ State-of-the-art approach
- ✓ Block matching method

C-PWC-Net

- ✓ Trained from synthetic datasets
- ✓ SyntheticMultiVendors and SyntheticCAMUS
- ✓ 11380 image pairs (A4C, A3C, A2C)

Results on the first dataset – GE – center n°1 – 30 patients

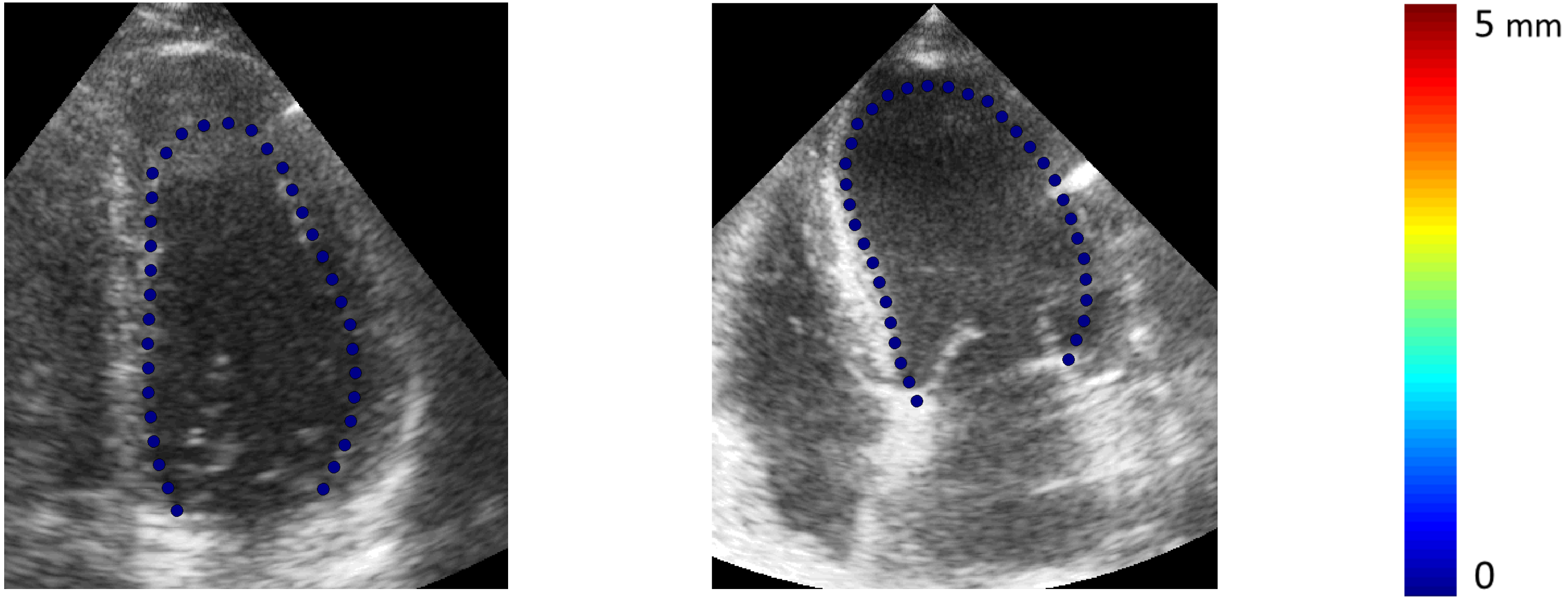
✓ Geometrical scores
(distance errors)

Methods	$d_m \pm \sigma$ (mm.)	$d_H \pm \sigma$ (mm.)
PIV	2.27 ± 1.30	5.36 ± 2.07
c-PWC-Net	$\mathbf{1.86 \pm 1.05}$	$\mathbf{3.81 \pm 1.18}$

✓ Clinical scores
(Mean absolute error)

Methods	GLS (%.)
PIV	7.35 ± 3.42
c-PWC-Net	$\mathbf{2.55 \pm 2.08}$

Results on the first dataset – GE – center n°1 – 30 patients



Distance Error

Results on the second dataset – Philips – center n°2 – 30 patients

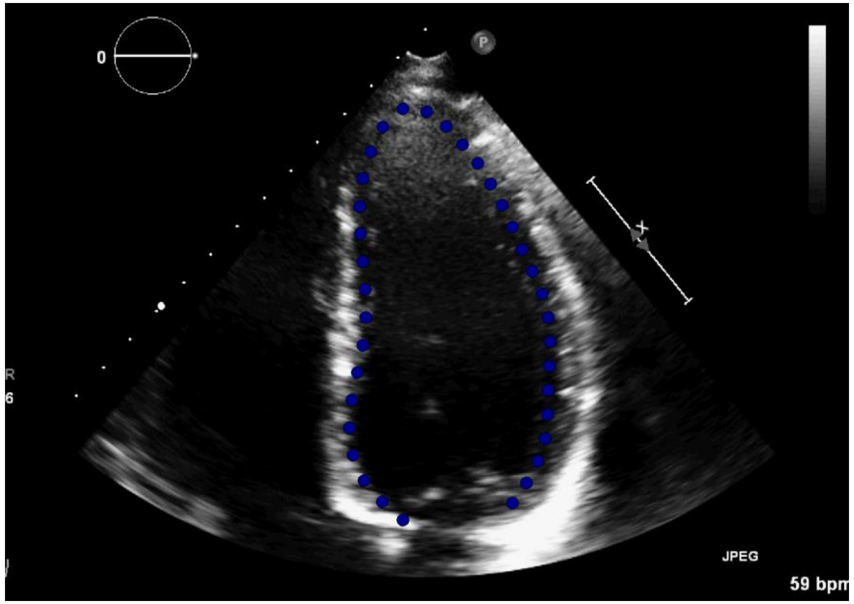
- ✓ Geometrical scores with cPWC-Net

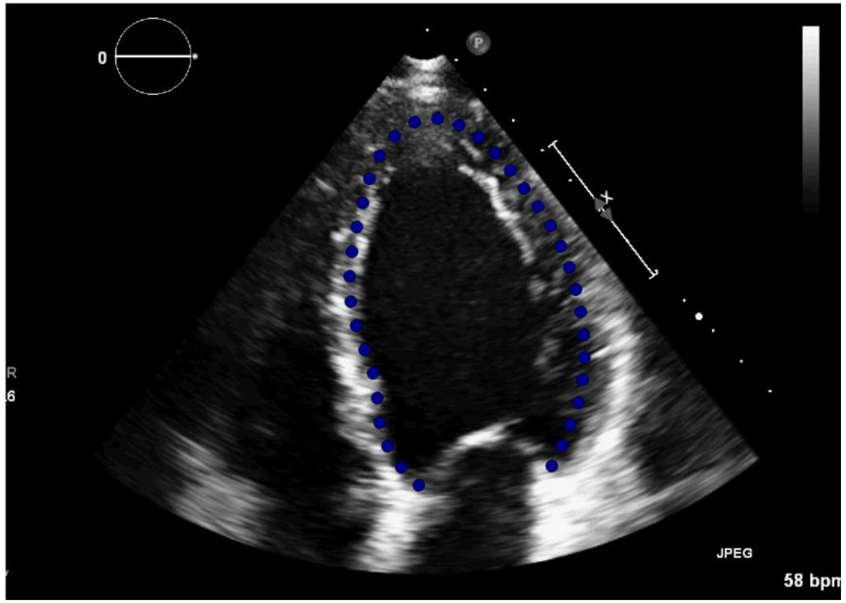
Philips dataset	$d_m \pm \sigma$ mm.	$d_H \pm \sigma$ mm.
Full dataset (#30)	1.81 ± 1.11	3.45 ± 1.11
Aortic Stenosis (#6)	1.72 ± 1.11	3.24 ± 1.02
Hypertrophic Cardiomyopathy (#6)	2.15 ± 1.26	3.91 ± 1.36
Ischemic (#6)	1.67 ± 1.08	3.38 ± 1.09
Non Ischemic (#6)	1.57 ± 0.95	3.03 ± 0.96
Normal (#6)	1.93 ± 1.14	3.69 ± 1.14

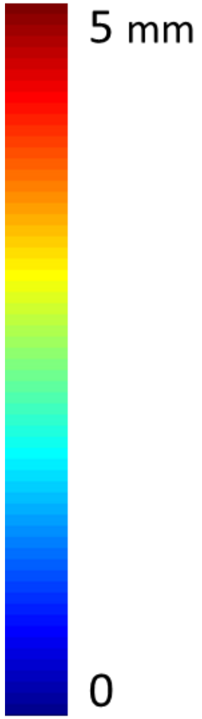
- ✓ Clinical scores with cPWC-Net

Philips dataset	***GLS*** %.
Full dataset (#30)	2.89 ± 2.08
Aortic Stenosis (#6)	2.85 ± 2.14
Hypertrophic Cardiomyopathy (#6)	3.33 ± 2.26
Ischemic (#6)	2.50 ± 1.56
Non Ischemic (#6)	2.01 ± 1.67
Normal (#6)	3.75 ± 2.84

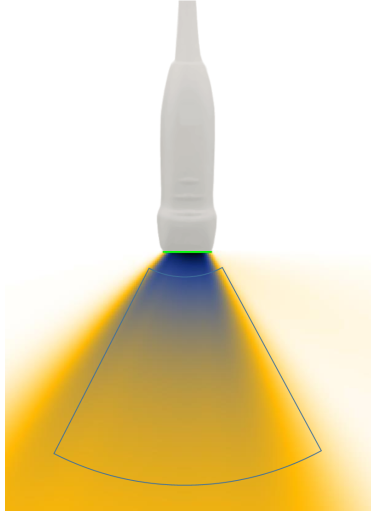
Results on the second dataset – Philips – center n°2 – 30 patients







Distance Error



Ultrafast cardiac imaging using deep learning

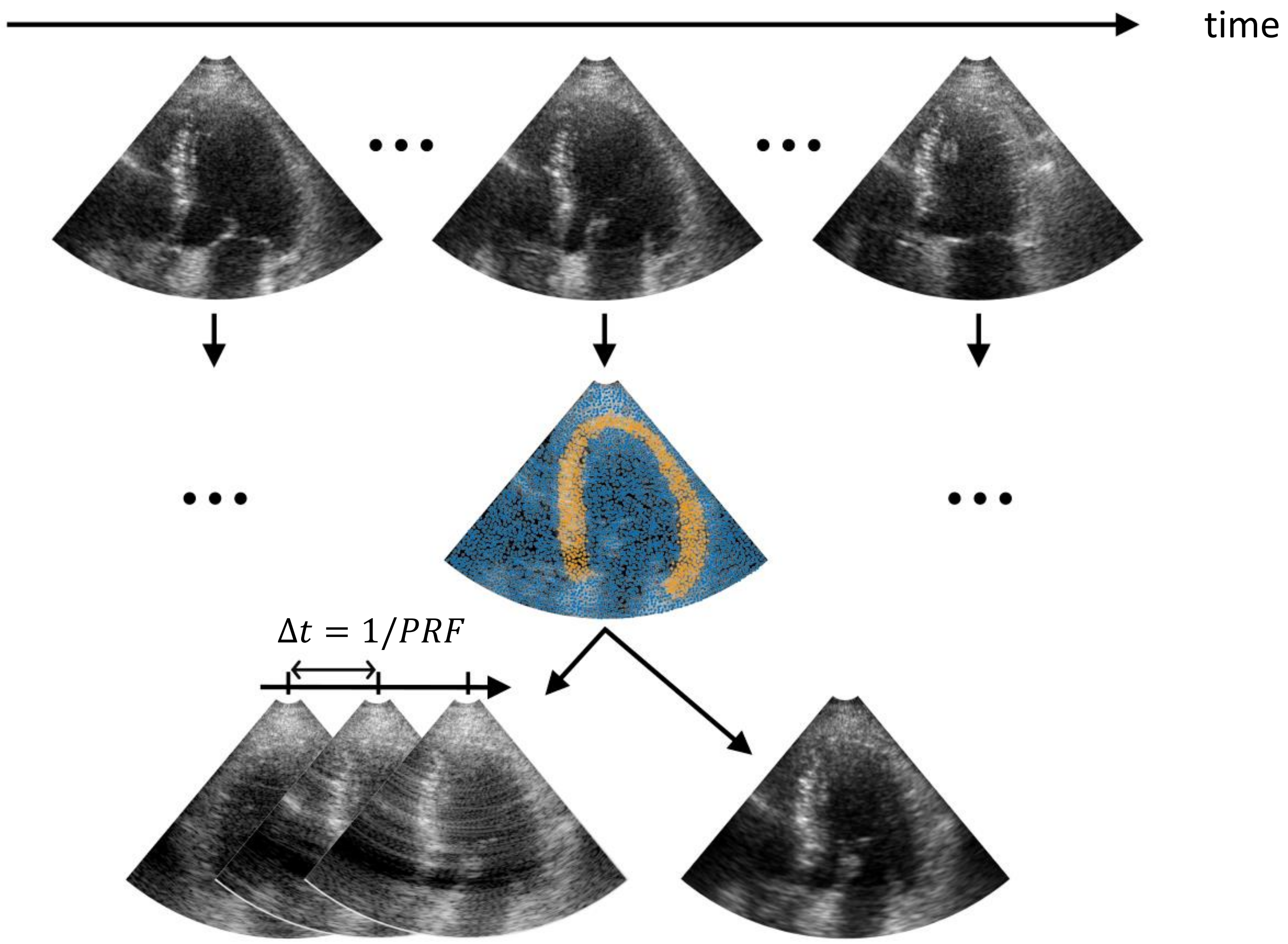
[Lu et al., IEEE IUS 2023]

Framework of cardiac imaging simulation

Real sequence

Scatterers maps at the PRF scale

Simulated DWs



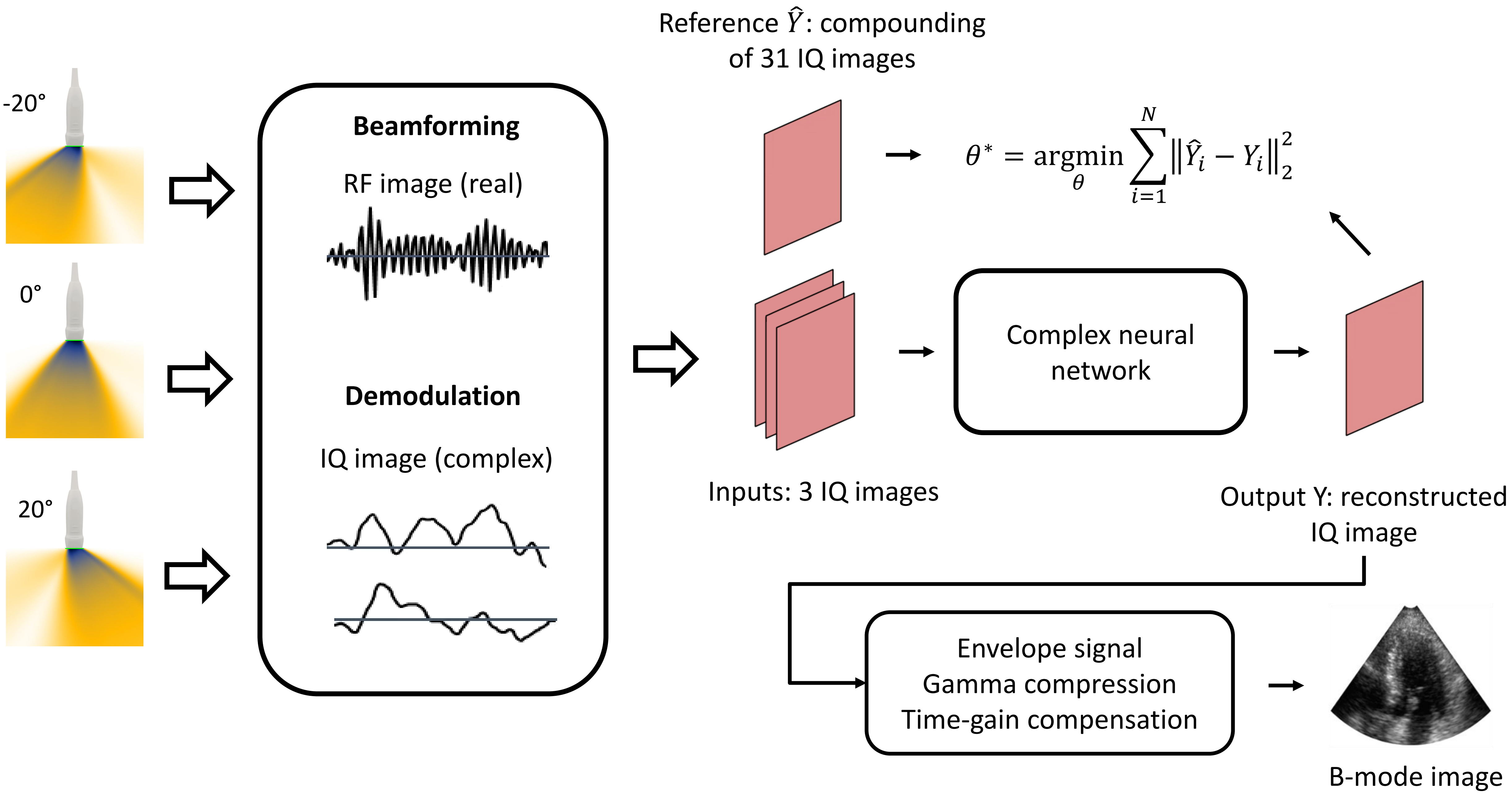
Dynamic transmissions: 3 successive angles along time

Compounding of 31 transmission angles at fixed time

Virtual cohort

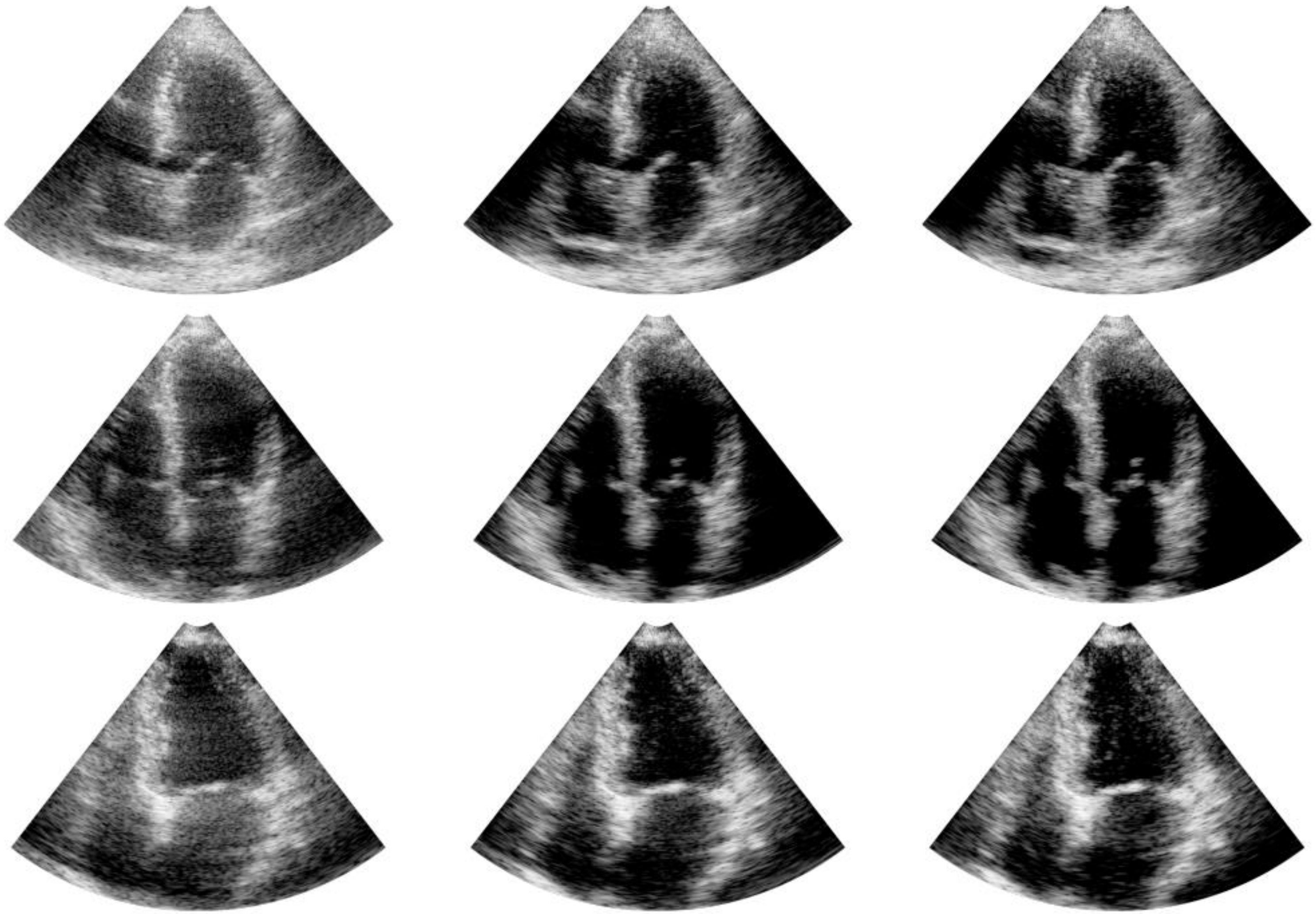
- ✓ 94 sequences in A4C
- ✓ 4344 frames with corresponding cardiac texture and myocardial displacement fields

Overall workflow

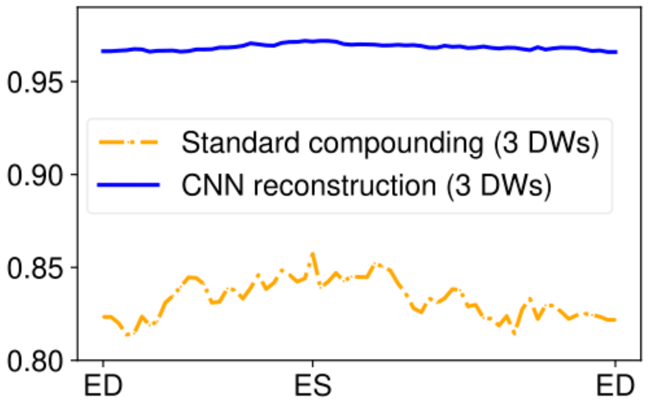


Results on the simulated sequences

Standard compounding (3 DWs) | CNN (3 DWs) | Compounding (31 DWs)

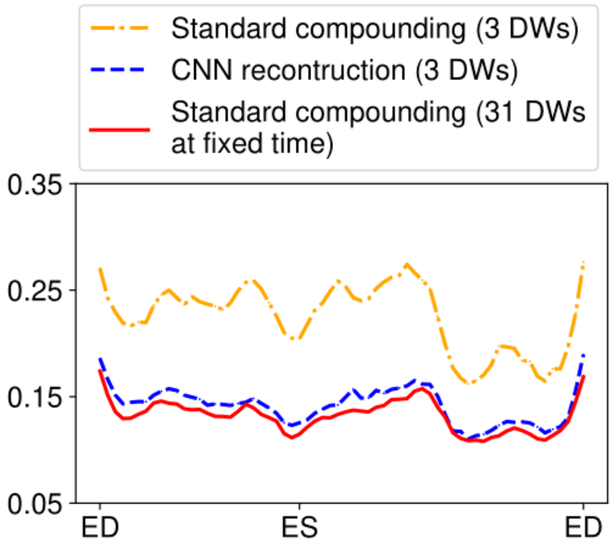


Structural Similarity Index



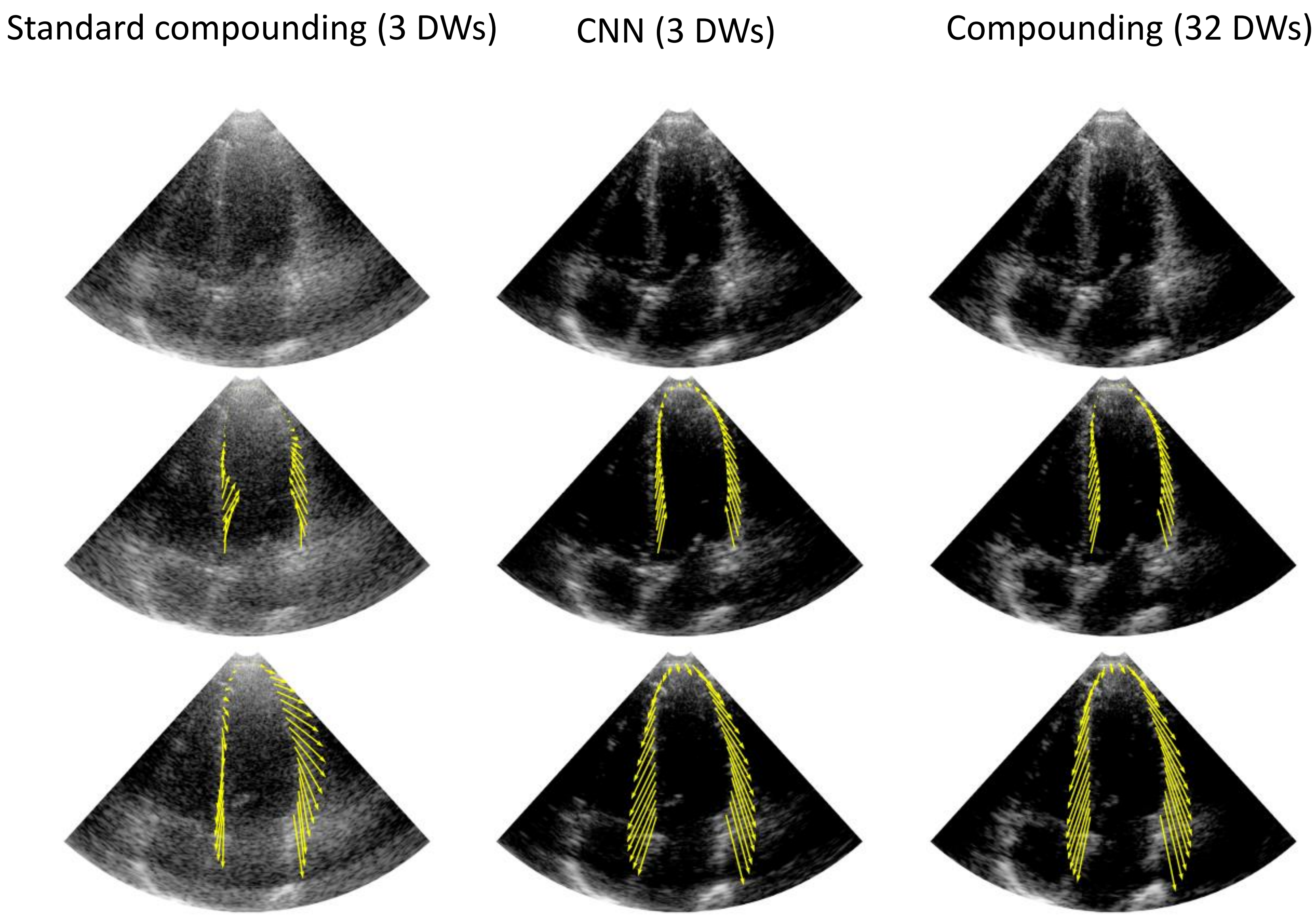
Frame number

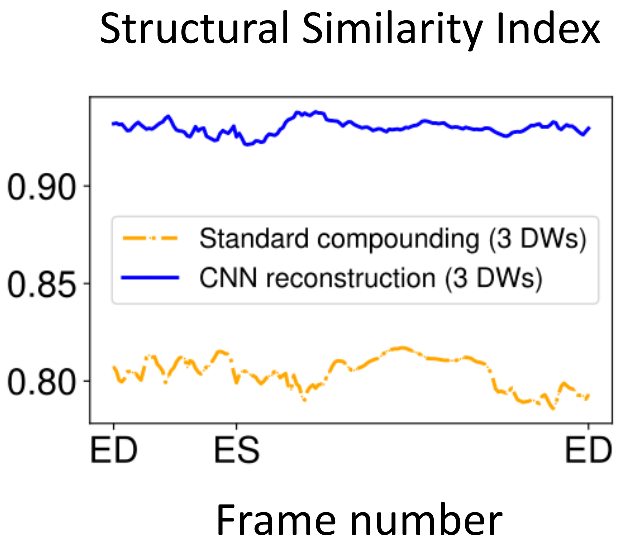
Mean End Point Error (mm)

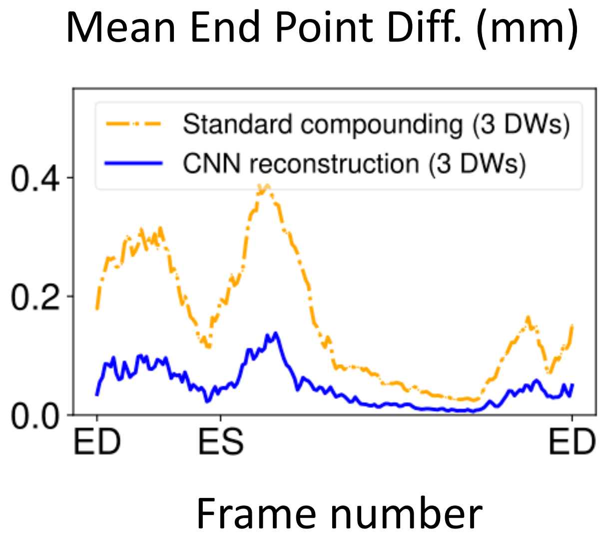


Frame number

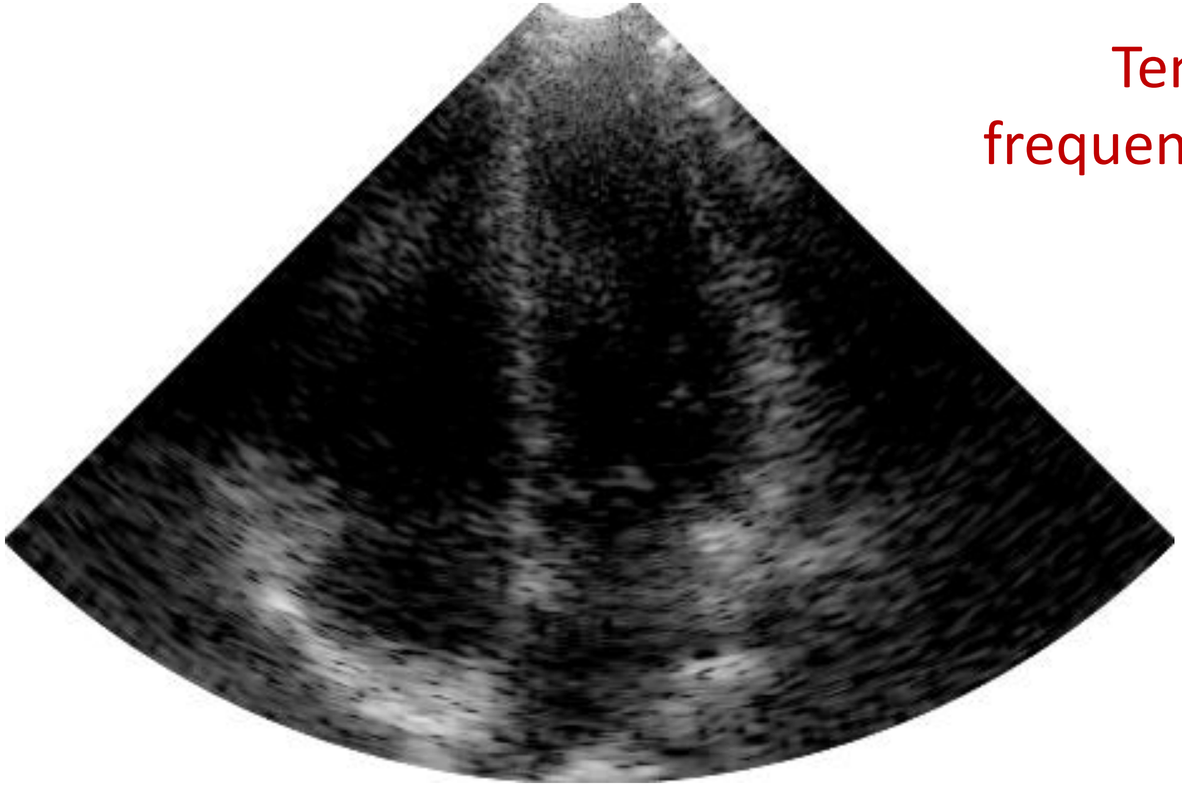
Results on the real sequences





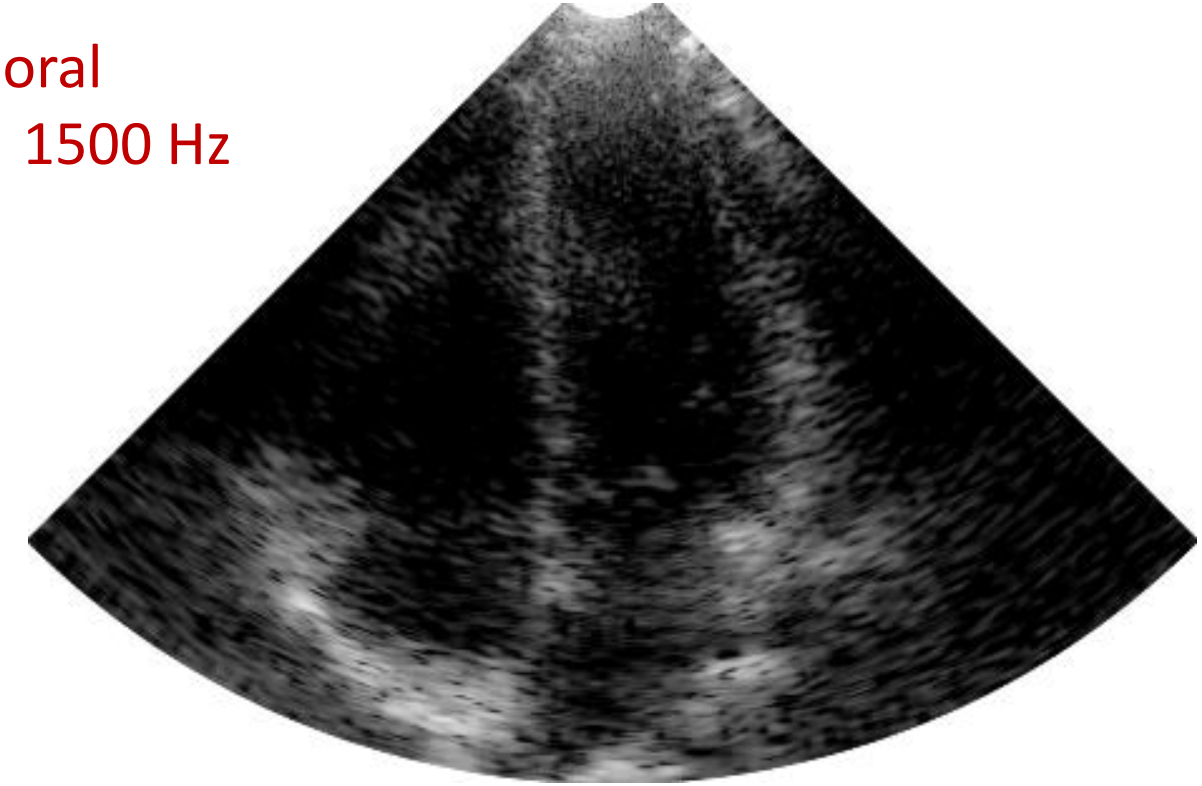


Towards ultrafast imaging



Fps / 40

Temporal frequency 1500 Hz



Fps /10

Conclusions & Perspectives

Conclusions & perspectives

- Conclusions
  - ✓ Learning from simulations alone is possible and effective !
  - ✓ Several synthetic datasets are already available

- Perspectives
  - ✓ Extension of the framework to simulate large-scale synthetic cohorts

> 100.000 patients

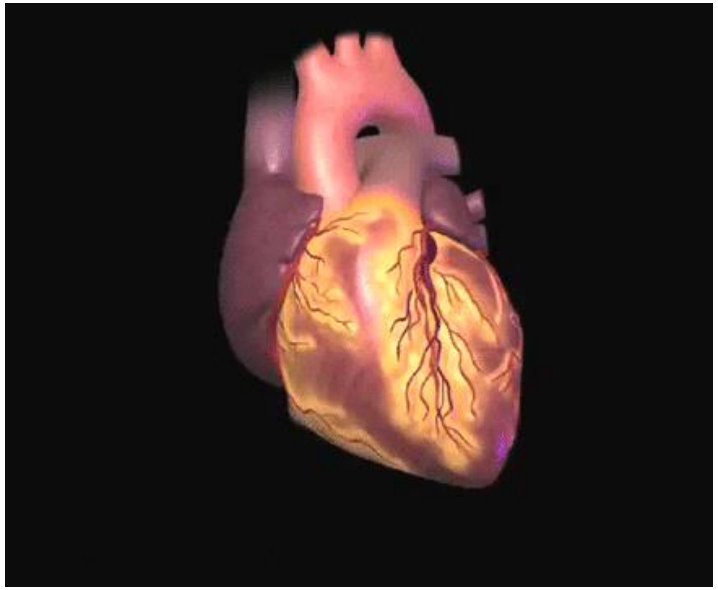
Thanks

Appendices

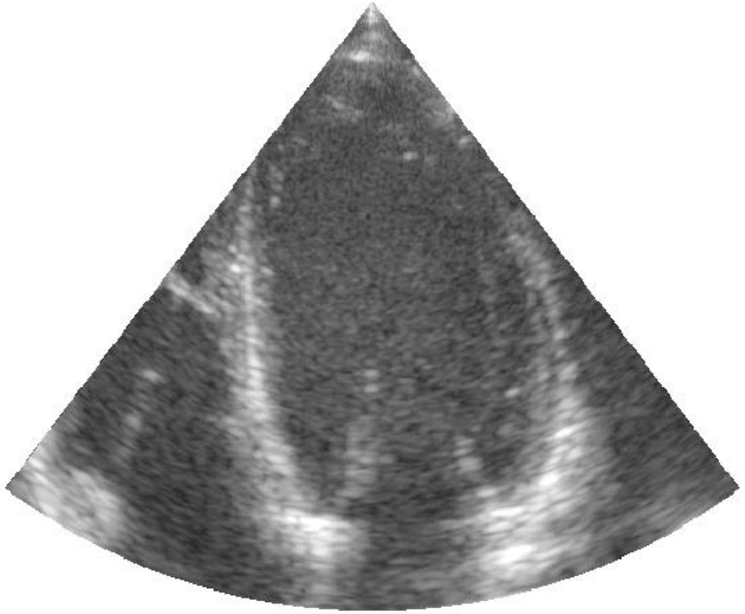
Echocardiographic imaging

Quantification of clinical indices to diagnose cardiac pathologies

- Anatomical imaging



Source: GE Healthcare web site



RF 2 IQ signals

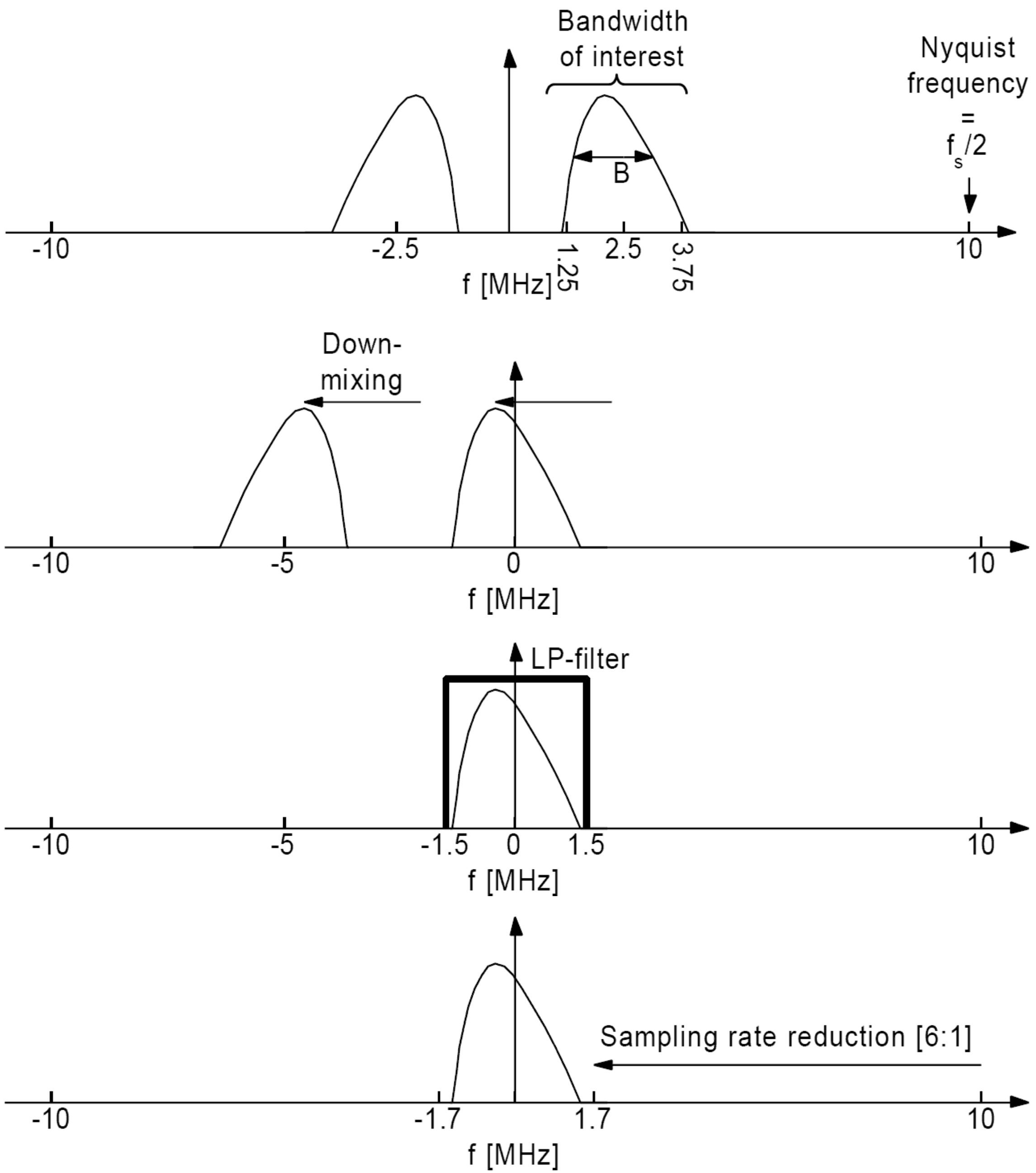
RF vs I/Q signal

RF spectrum

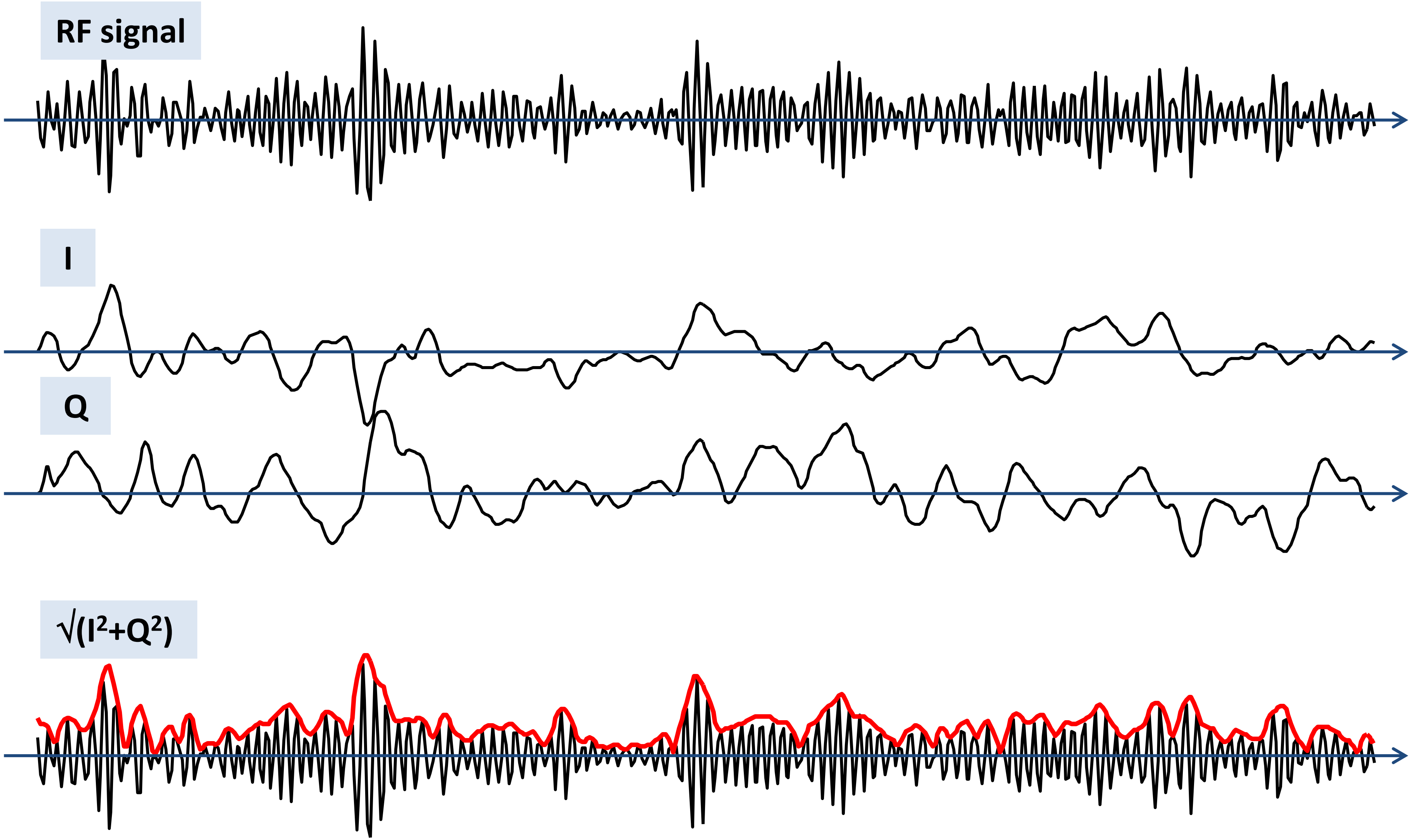
Down-mixing

Low pass filtering

Downsampling



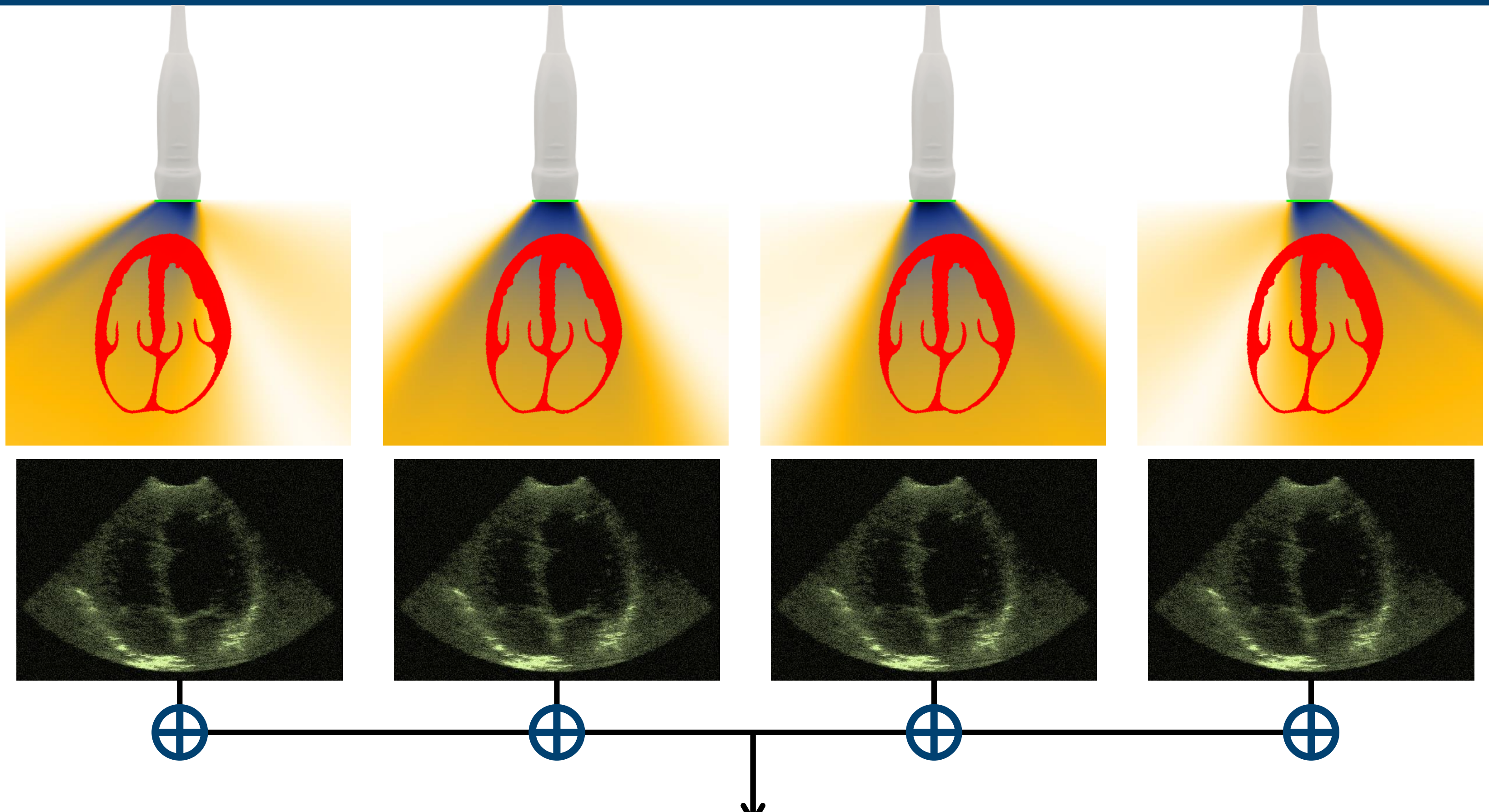
RF vs I/Q signal



Coherent compounding

32 firings

Poor quality
individual images



High-contrast
High-resolution

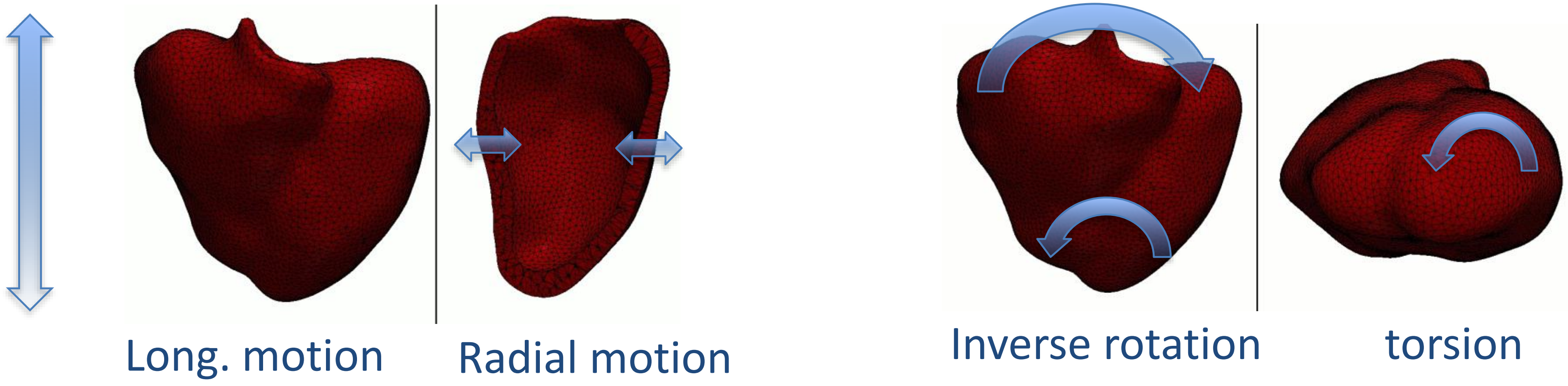
Patient-based B-mode echocardiographic simulation for validation of myocardial motion estimation

[Alessandrini et al., IEEE TMI 2018]

Displacement of myocardial point scatterers

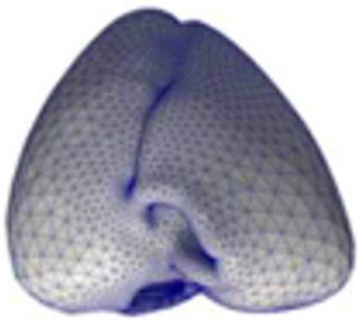
Electromechanical model (from INRIA, Epione team)

- ✓ Electrical activation / Mechanical contraction
- ✓ Biophysical parameters: contractility, stiffness, conduction
- ✓ Possibility of introducing controlled pathological movements

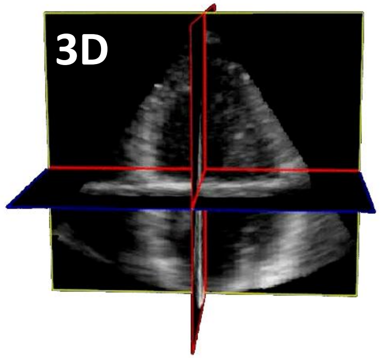


Courtesy of Maxime Sermesant, INRIA, France

Personalization procedure

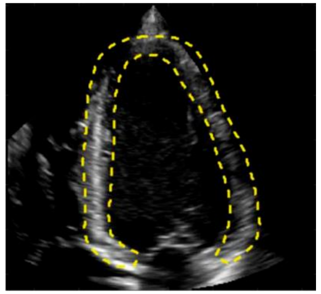


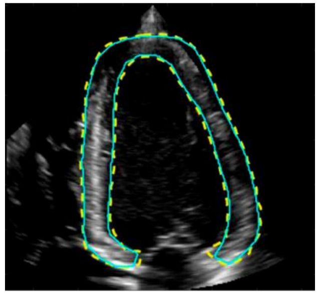
Semi-automatic segmentation



1 EM model / real 3D US sequence registration

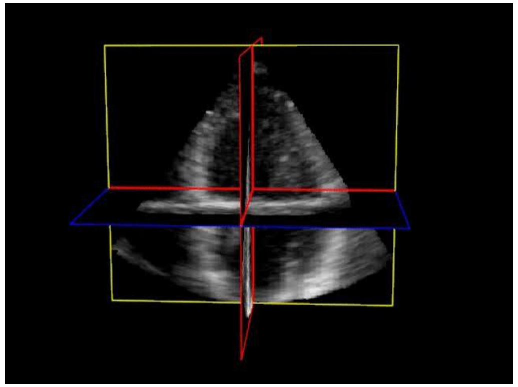
Semi-automatic segmentation



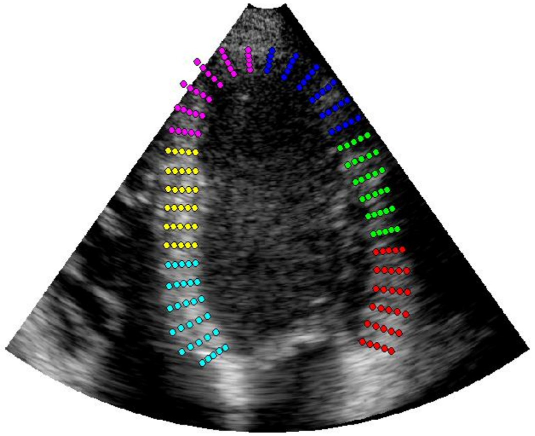


2 Real 3D sequence / 2D US sequence registration

$\boldsymbol{\phi_1}(\cdot)$



$\boldsymbol{\phi_2}(\boldsymbol{\phi_1}(\cdot))$

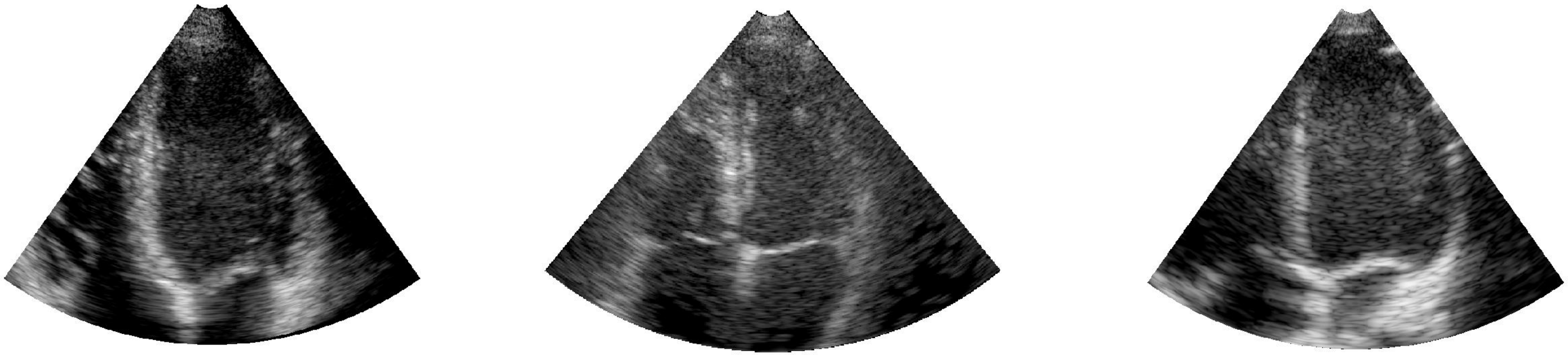


B-mode sequence simulation workflow

Virtual cohort

- ✓ SyntheticMultiVendors - open access dataset
- ✓ 7 different vendors, 3 views (A3C, A4C, A2C) per vendor
- ✓ 1 healthy subject + 4 pathologies per view (lcx, laddist, ladprox, rca)

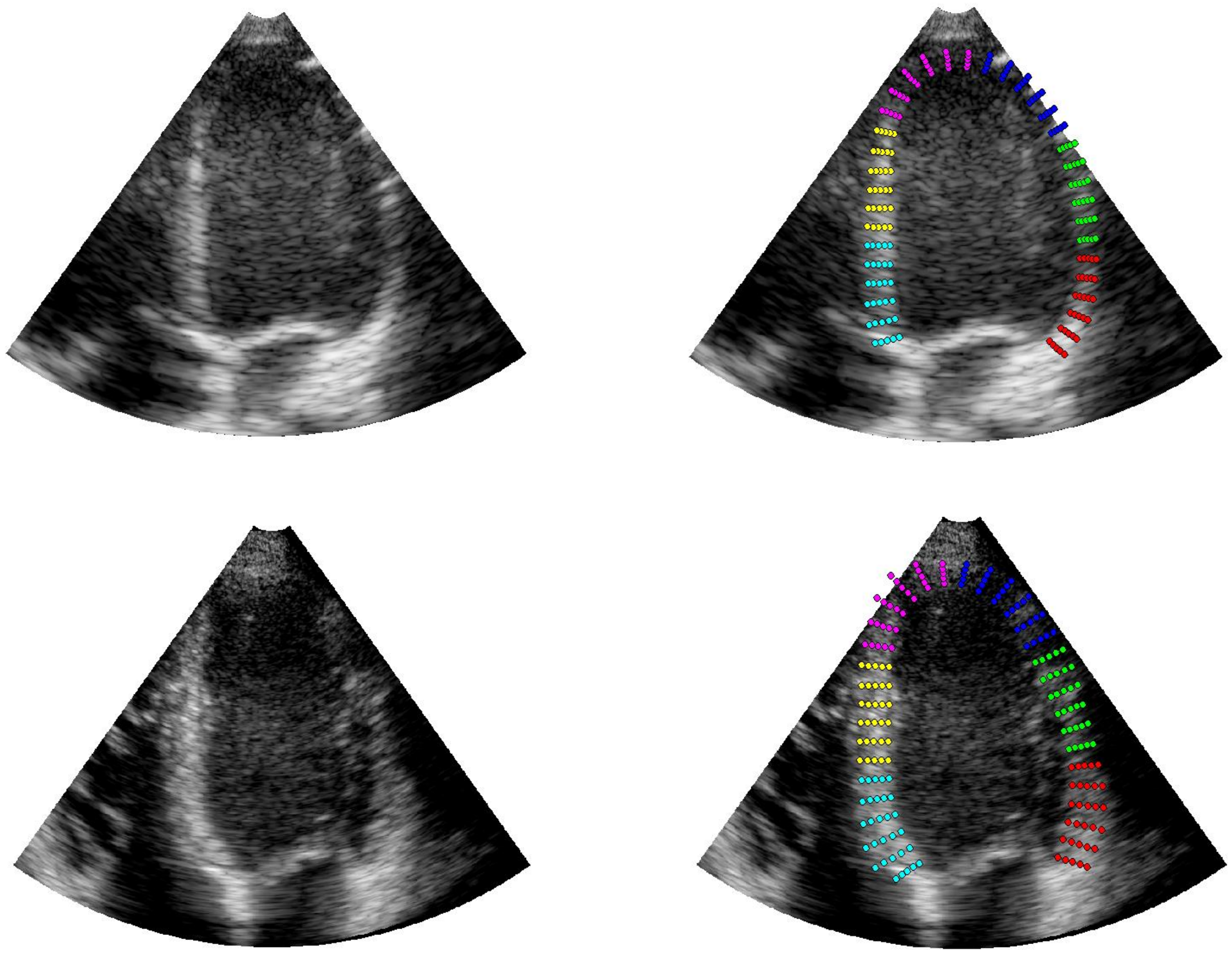
https://gbiomed.kuleuven.be/english/research/50000635/50508167/open-data



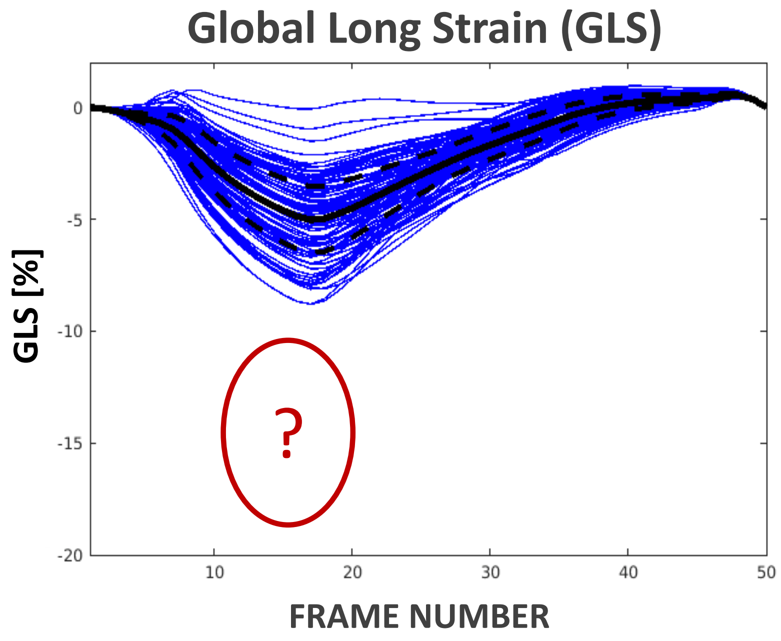
SyntheticMultiVendors dataset - properties

Simulated B-mode sequences

Simulated B-mode sequences with meshes



Realistic analytical motion model for validation



Simple remeshing strategy

Motivations: match easily the myocardial anatomy and motion of any patients

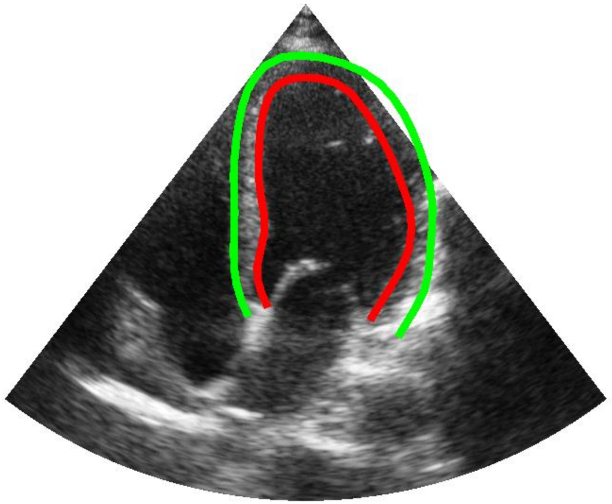
- ✓ Ability to simulate large-scale synthetic dataset
- ✓ Simulation of a wide range of myocardial deformations

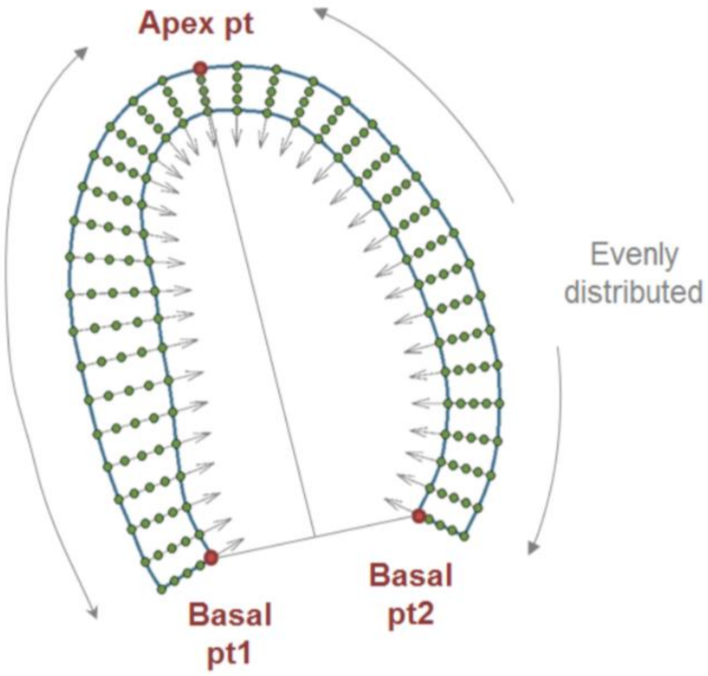
Real sequence

Simulated sequence

Displacement of myocardial point scatterers

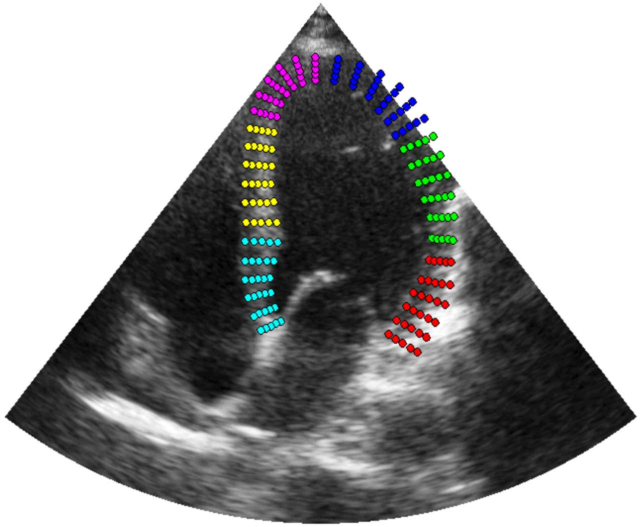
Manual annotation or automatic segmentation





Myocardial mesh generation for each contour

Sequence of myocardial meshes



Synthetic motion with locally affine displacements

B-mode sequence simulation workflow

Virtual cohort

- ✓ SyntheticCAMUS - open access dataset
- ✓ 98 simulated sequences in A4C
- ✓ Download at humanheart-project webiste

https://humanheart-project.creatis.insa-lyon.fr/database/#collection

Ultrasound physical simulator

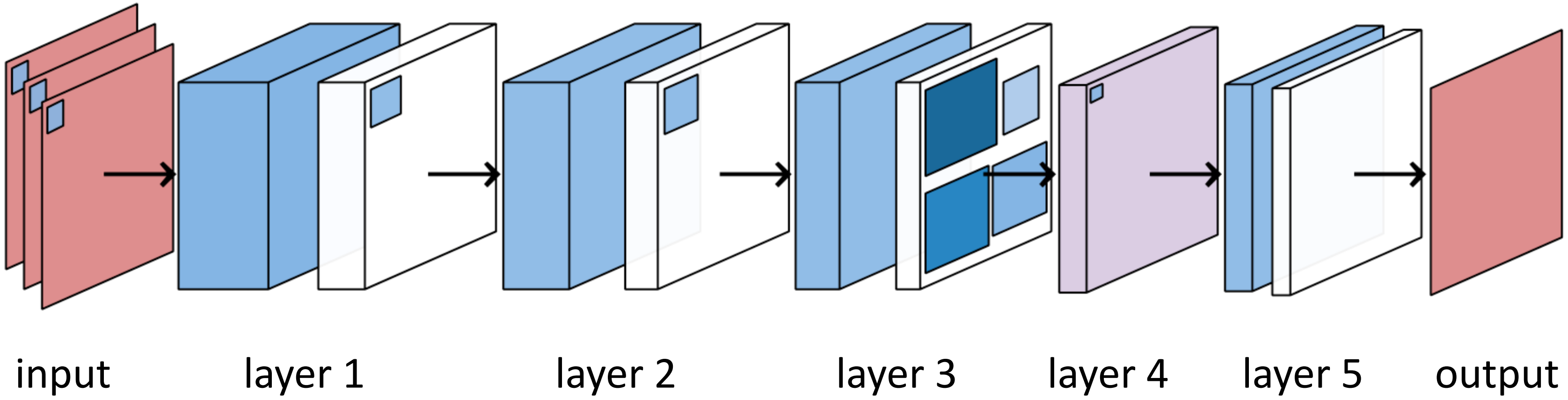
Several existing solutions

- ✓ Field II
- ✓ k-Wave
- ✓ Verasonics
- ✓ SIMUS [Garcia et al., CMPB 2022]

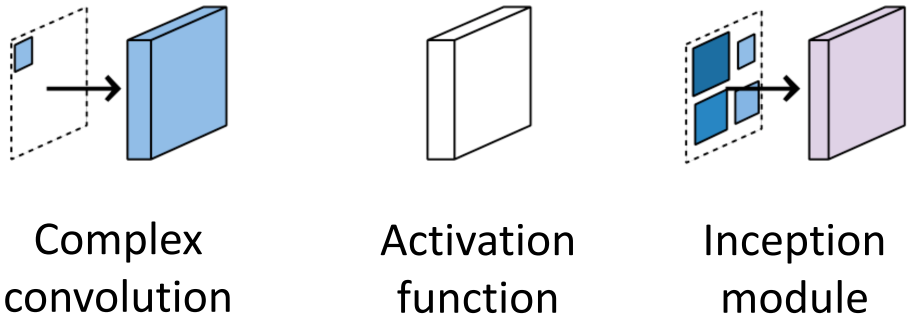
Most of them based on the same strategy

- ✓ Modeling of the emitted field (linear propagation)
- ✓ Modeling of the insonified medium through point scatterers

Complex neural network



3 key properties



Complex convolution

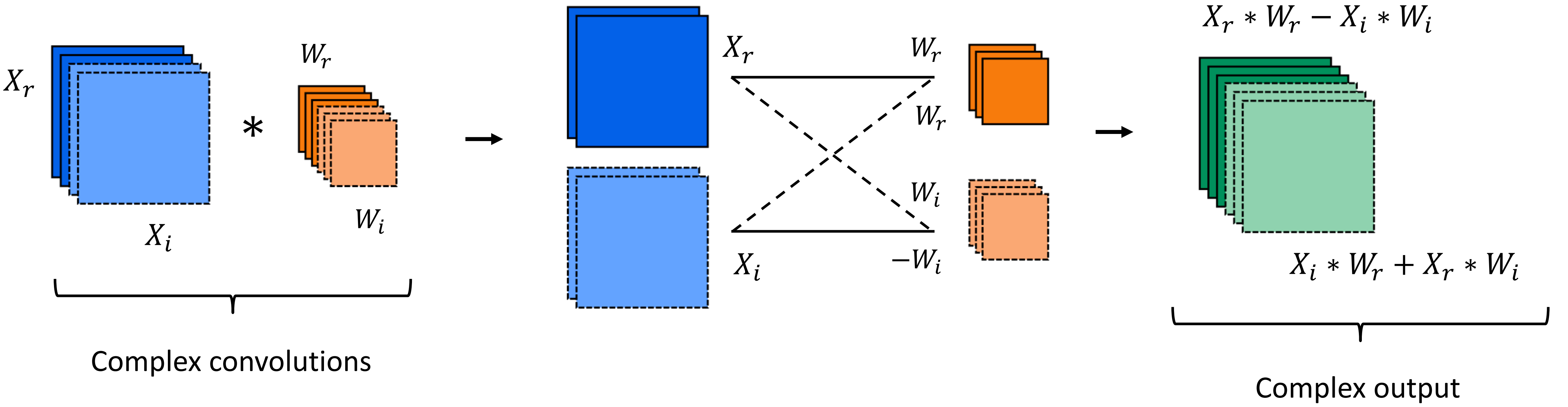
Complex feature maps $X = X_r + jX_i$

Complex kernels $W = W_r + jW_i$

$$\xrightarrow{Z = X * W}$$

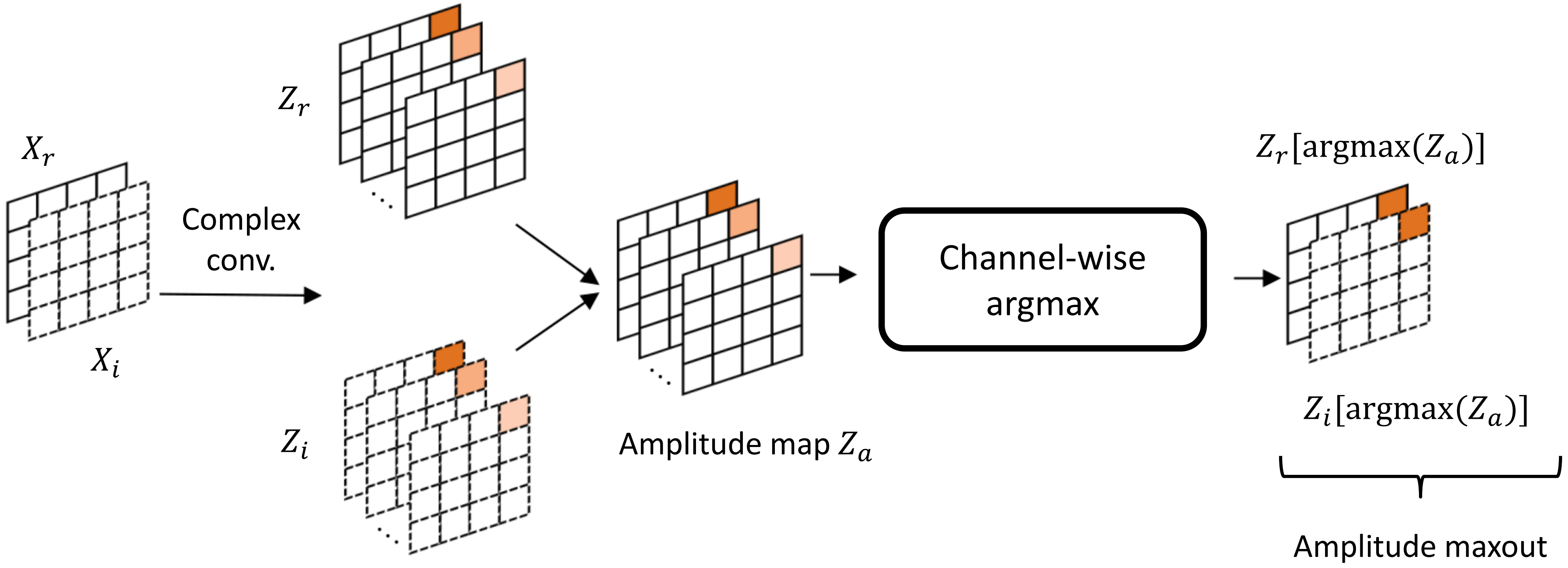
$$Z = X * W = (X_r + jX_i) * (W_r + jW_i)$$

$$Z = (X_r * W_r - X_i * W_i) + j(X_i * W_r + X_r * W_i)$$



Activation function

AMU: Amplitude Maxout Unit

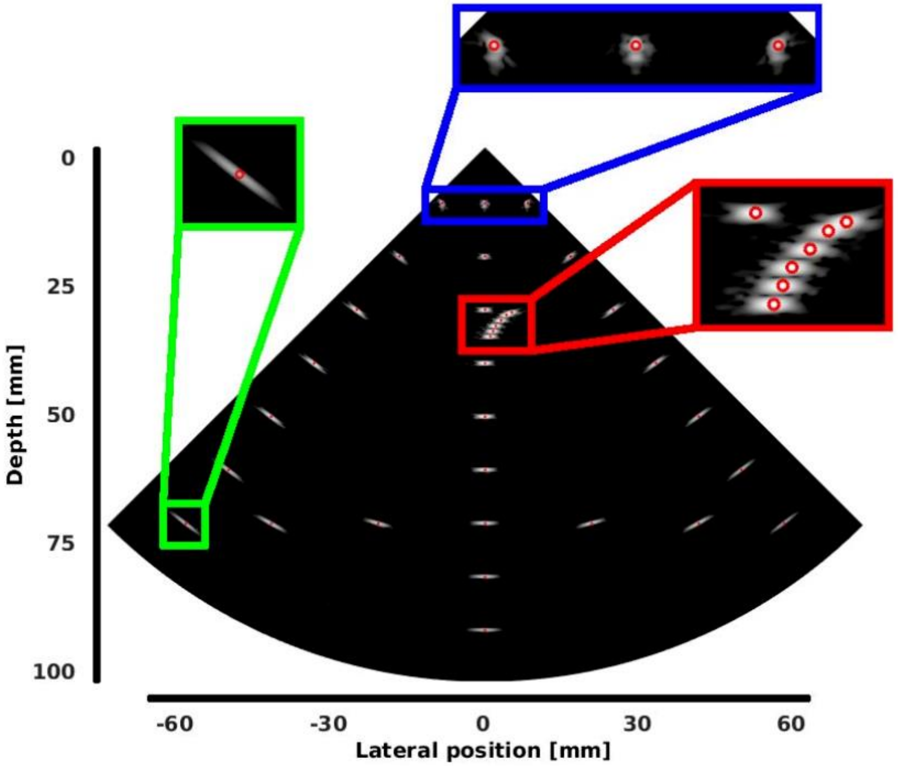


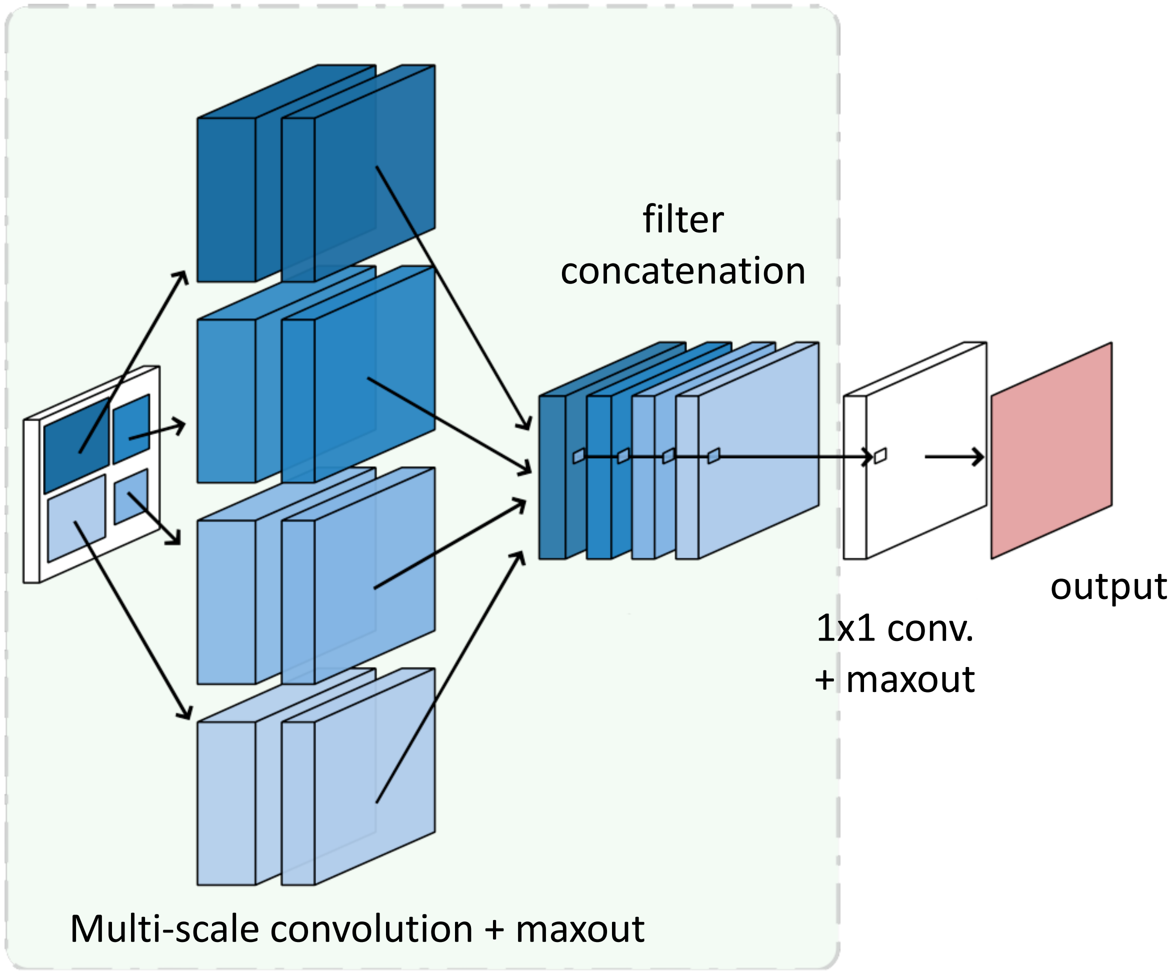
- ✓ Preserves magnitude and phase of signals throughout the complex plan
- ✓ Does not change the differentiability of complex convolutions

Inception module

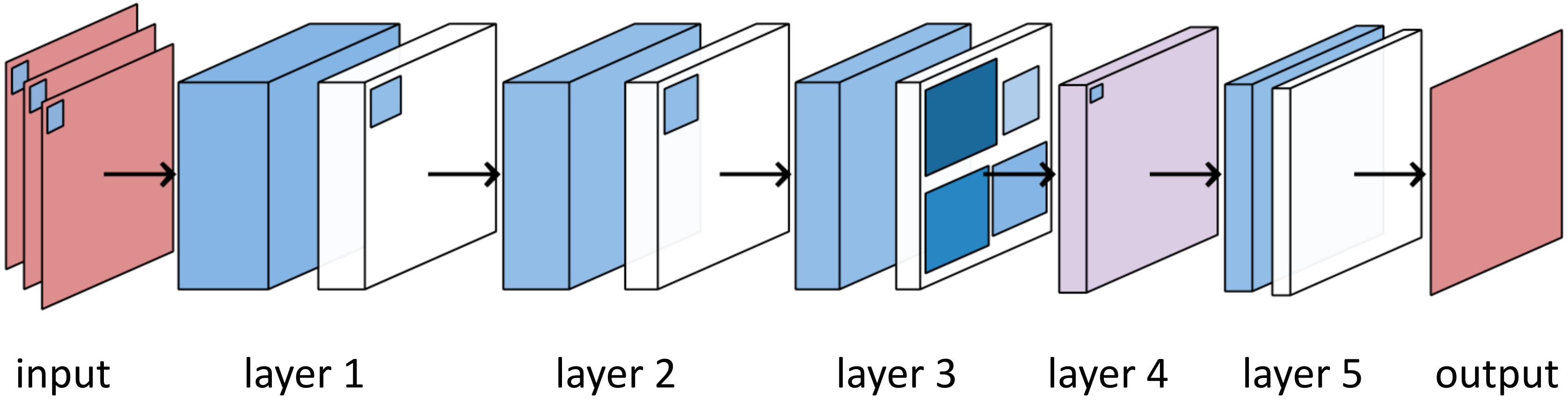
Interest

✓ Deal with spatial varying properties of US images





Complex neural network



Feature size	Kernel size	Kernel number	Activation
$m \times h \times w$	–	–	–
$64 \times h \times w$	3×3	256	4-piece AMU
$32 \times h \times w$	5×5	128	4-piece AMU
$16 \times h \times w$	9×9	64	4-piece AMU
$8 \times h \times w$	11×11	8	4-piece AMU
	13×13	8	4-piece AMU
	15×15	8	4-piece AMU
	17×17	8	4-piece AMU
$1 \times h \times w$	1×1	4	4-piece AMU