A Deep Learning Approach to Ultrasound Image Recovery

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Outline

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Introduction

Context

- Ultrasound (US) system design is pushing towards portability
- ADCs are incorporated in the probe head ➔ digital interface (e.g. wireless)
  - ⚠ **data transfer issues (esp. for ultrafast US imaging)**
  - ☺ **can “easily” add compression capability in the probe head**

Objective

- Recovering US signals from undersampled measurements
- In real time (if possible ☺) ➔ **fast compression and recovery**

Great candidate ➔ compressed sensing (CS)

- Provides a way to exactly recover a signal from undersampled measurements, under very specific assumptions (sparsity and RIP)[1]
- Main drawbacks:
  - Sparsity of US signals is very hard to obtain (esp. inside speckle regions)
  - Use of convex optimization algorithms (hundreds of iterations) ➔ **slow**

[1] http://statweb.stanford.edu/~markad/publications/ddek-chapter1-2011.pdf

Stacked Denoising Autoencoders (SDA)

- A DNN architecture successfully applied to **structured signal recovery**[2]
- Compression is considered as the first layer of the proposed architecture
- Recovery is performed by the hidden and output layers
- Two measurement cases are explored:
  1. **SDA–CNL**: Linear measurement case where the **compression is not learned**
  2. **SDA–CL**: Non-linear measurement case where the **compression is learned**

Imaging pipeline

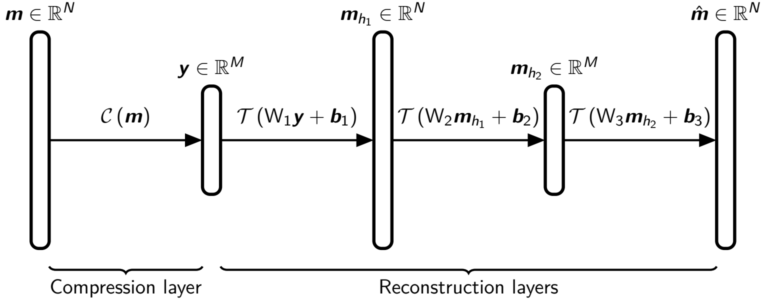
- Once trained, the first layer is used to compress each of the element-raw-data signals **independently**, the remaining layers are used for the recovery
- Both operations can be performed **in parallel** for all channels ➔ **fast** ☺
- The US image is then retrieved using any image reconstruction algorithm

[2] https://arxiv.org/abs/1508.04065

Deep learning for ultrasound image recovery

Proposed architectures

SDA with 4 fully-connected layers



Reconstruction layers

$\mathrm{W}_1 \in \mathbb{R}^{N\times M}$
$\boldsymbol{b}_1 \in \mathbb{R}^N$
$\mathrm{W}_2 \in \mathbb{R}^{M\times N}$
$\boldsymbol{b}_2 \in \mathbb{R}^M$
$\mathrm{W}_3 \in \mathbb{R}^{N\times M}$
$\boldsymbol{b}_3 \in \mathbb{R}^N$
$\mathcal{T}(\,.\,) = \tanh(\,.\,)$

Compression layer

- SDA–CNL: $\mathcal{C}(\boldsymbol{m}) = \Phi\boldsymbol{m}$, where $\Phi \in \mathbb{R}^{M\times N}$ is a random Gaussian matrix, **not learned** during training
- SDA–CL: $\mathcal{C}(\boldsymbol{m}) = \mathcal{T}(\mathrm{W}_{in}\boldsymbol{m} + \boldsymbol{b}_{in})$, where $\mathcal{T}(\,.\,) = \tanh(\,.\,)$, $\mathrm{W}_{in} \in \mathbb{R}^{M\times N}$ and $\boldsymbol{b}_{in} \in \mathbb{R}^M$, **learned** during training

Acquisition configuration

- Plane-wave imaging challenge in medical ultrasound (PICMUS)[3]

Parameter	**L11-4v**
Element number	128
Pitch	300 µm
Center frequency	**5.133 MHz**
Bandwidth	**67 %**
Element width	0.27 mm
Transmit frequency	5.208 MHz
Excitation	2.5 cycles
Sampling frequency	**20.832 MHz**

- Sampling frequency **extremely close to the Nyquist frequency** of US signals
- The sample number N is fixed to 1024 to fit typical DNN sizes

[3] https://www.creatis.insa-lyon.fr/EvaluationPlatform/picmus/index.html

Training set

- Simulated using the open-source k-Wave toolbox[4]
- $c_0 = 1540\,\mathrm{m\,s^{-1}}$, $Z_0 = 1.63 \times 10^6\,\mathrm{kg\,m^{-2}\,s^{-1}}$, $\alpha = 0.5\,\mathrm{dB\,MHz^{-1}\,cm^{-1}}$
- Simulation accounts for the element directivity
- Insonified medium is randomly generated from 3 main components:
  1. A fully diffusive background (echogenicity reference)
  2. 1 to 3 circular inclusions (random position) of variable radius and echogenicity:
     - Radius: drawn between 5 and 50 wavelengths
     - Echogenicity: anechoic (80 %) || −6 dB to 6 dB (15 %) || 10 dB to 20 dB (5 %)
  3. 0 to 5 point reflectors (random position)
- Transmit scheme: single PW insonification
- Each simulated acquisition is composed of 128 raw-data
- 20 000 simulated acquisitions ➔ **2.5 M element-raw-data signals**

[4] http://www.k-wave.org

Training set-up

- Implementation[5]: TensorFlow
- TGC is applied to raw-data
- Data normalized between -1 and 1 to fit the range of the non-linearity
- The training is performed on a NVIDIA GeForce GTX 1080 Ti
- Learning rate: 0.001
- Epoch number: 20 epochs
- Mini-batch learning with a batch size of 4096

Training set-up (cont.)

- Initialization:
  - Weights ➔ Xavier
  - Biases ➔ zero
- Optimizer: Adam
- Loss function: ℓ_2-loss
- Undersampling ratio M/N ranging from 0.05 to 0.5

[5] https://github.com/dperdios/us-rawdata-sda

Three approaches are compared

1. SDA–CNL: comp. Gaussian matrix, rec. 3 layers
2. SDA–CL: comp. learned, rec. 3 layers
3. A CS reconstruction based on a sparsity prior in a convolutional dictionary made of shifted pulses: comp. Gaussian matrix, rec. PDFB (1000 iterations)

Test set ➔ PICMUS datasets

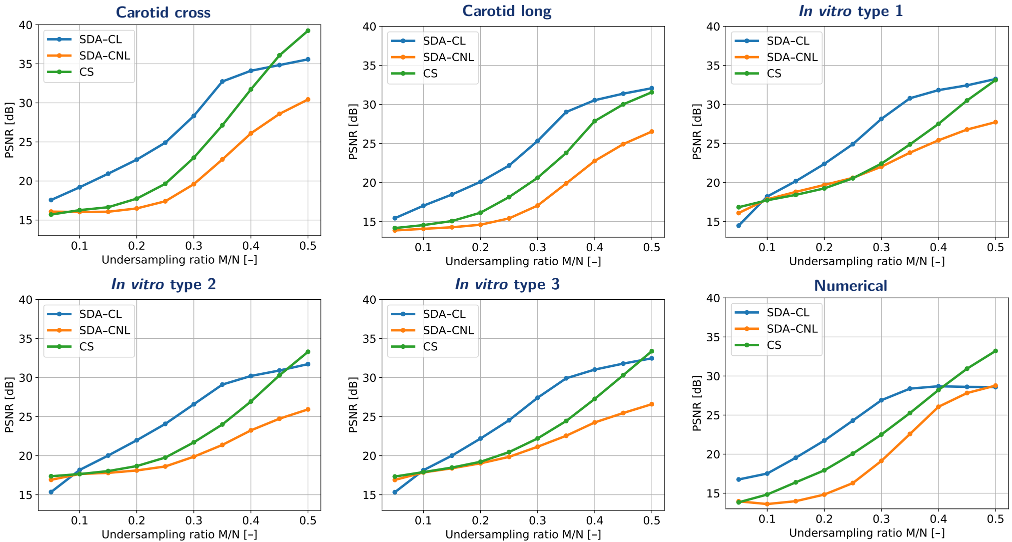
- 1 numerical image (PICMUS 2017)
- 3 *in vitro* images (PICMUS 2017)
- 2 *in vivo* images (PICMUS 2016)

Performance evaluation

- DAS (spline + elem. directivity) is performed on recovered signals ➔ RF image
- Envelope extraction ➔ normalization ➔ log-compression ➔ B-mode image
- PSNR on B-mode images (40 dB for *in vivo*, 60 dB for numerical and *in vitro*)

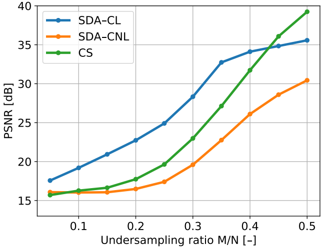
Results

Performance evaluation on the PICMUS dataset



Results

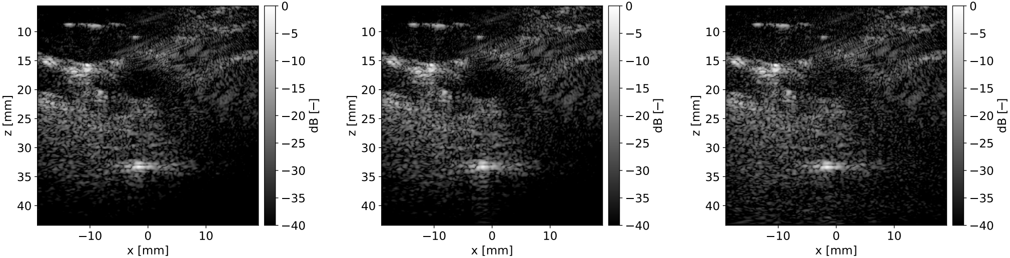
Visual assessment – Carotid cross



Reference (100 %)

SDA–CL (30 %)

CS (30 %)



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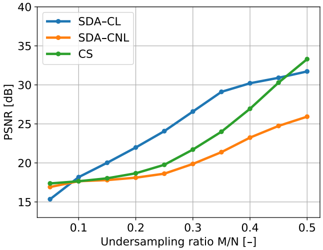
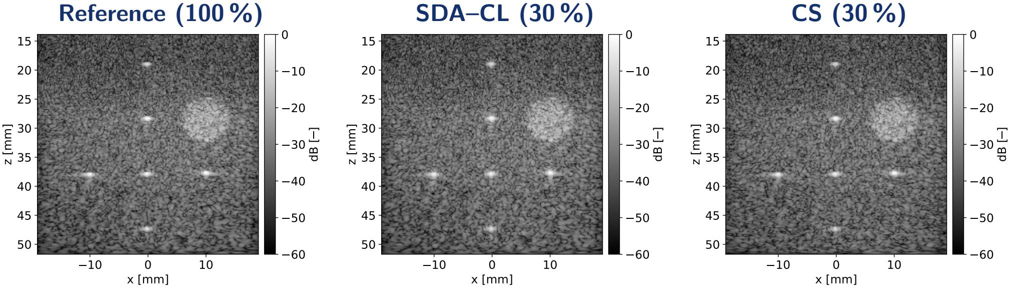
Results
Visual assessment – *In vitro* type 2





Conclusion

Compression capability

- Reference data extremely close to the Nyquist frequency
- Good recovery with 30 % of the data

Reconstruction complexity

- CS: $\geq 2 \times 1000 \times \mathcal{O}(MN)$
- SDA–CL: $3 \times \mathcal{O}(MN)$
- Almost **1000 times faster than CS**

Quality

- SDA–CL outperforms CS at low undersampling ratios
- Quite robust to variable image regions (speckle, anechoic, etc.)

Current drawbacks and future work

- Low generalizability: trained for 1024 time samples
- Seems to suffer from oscillating artifacts around hyperechoic regions
- Side information across the transducer elements is not exploited

THANK YOU FOR YOUR ATTENTION!

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