From Compressed Sensing to Deep Learning: Tasks, Structures, and Models

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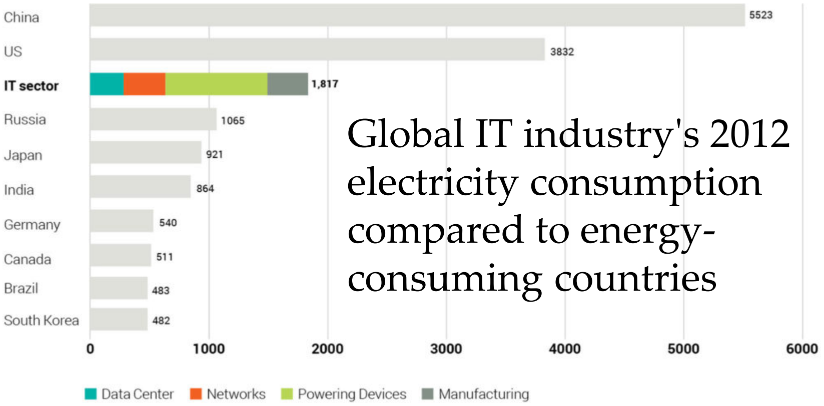
WEIZMANN INSTITUTE OF SCIENCE

SAMPLLAB
Signal Acquisition Modeling Processing and Learning

Data Abundancy

Challenges of data proliferation in the digital era:

- Power
- Storage
- Processing
- Communicating



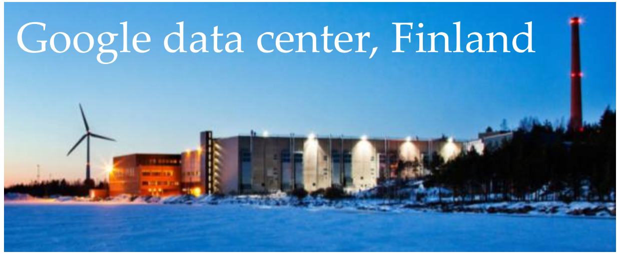
Global IT industry's 2012 electricity consumption compared to energy-consuming countries

AI

10^{21}

Cisco: Mobile internet traffic will approach a zettabyte by 2022

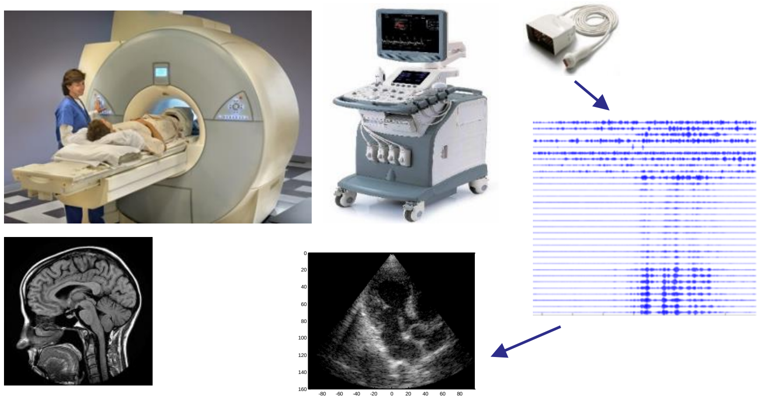
KYLE WIGGERS @KYLE_L_WIGGERS FEBRUARY 19, 2019 5:00 AM



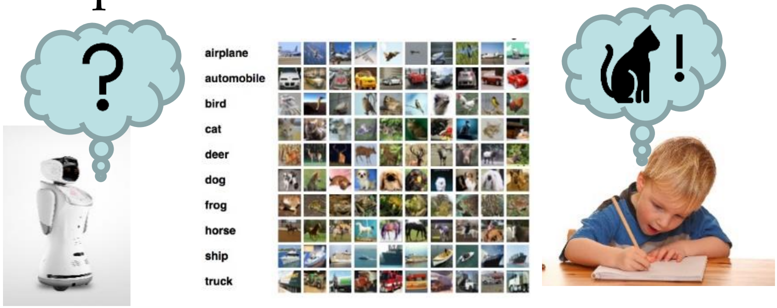
Do we really need so much data?

Data Redundancy

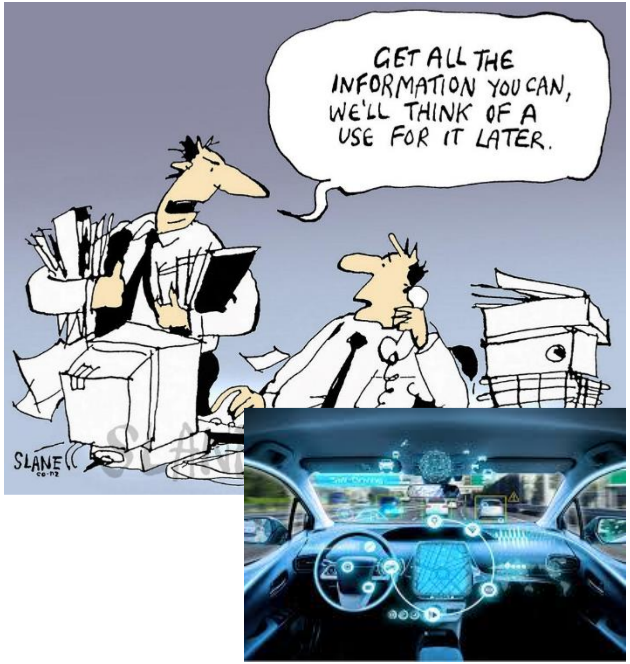
Medical imaging



Deep neural networks



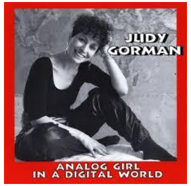
Smart cities, autonomous cars



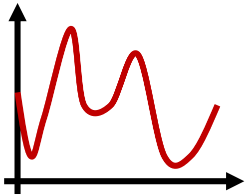
Can we acquire only what we need?

“Analog Girl in a Digital World…”

Judy Gorman 99



Analog world

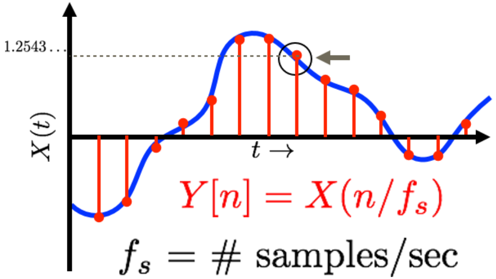


$x(t)$

- Music
- Radar
- Communication
- Image…

Sampling

Analog-to-Digital Convertor (ADC)



$R = f_s \log_2(\#\text{of levels})$ (bit/sec)

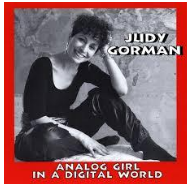
Digital world

$y[n]$ 010010110

- Signal processing
- Image denoising
- Compression…

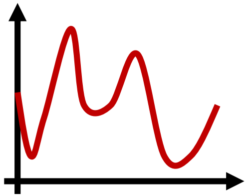
“Analog Girl in a Digital World…”

Judy Gorman 99



Analog world	Sampling	Digital world

Analog world



$x(t)$ →

- Music
- Radar
- Communication
- Image…

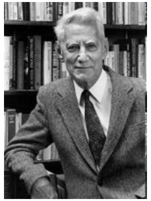
Sampling

Analog-to-Digital Convertor (ADC)

Sampling rate at least **twice** the highest frequency

H. Nyquist

C. Shannon

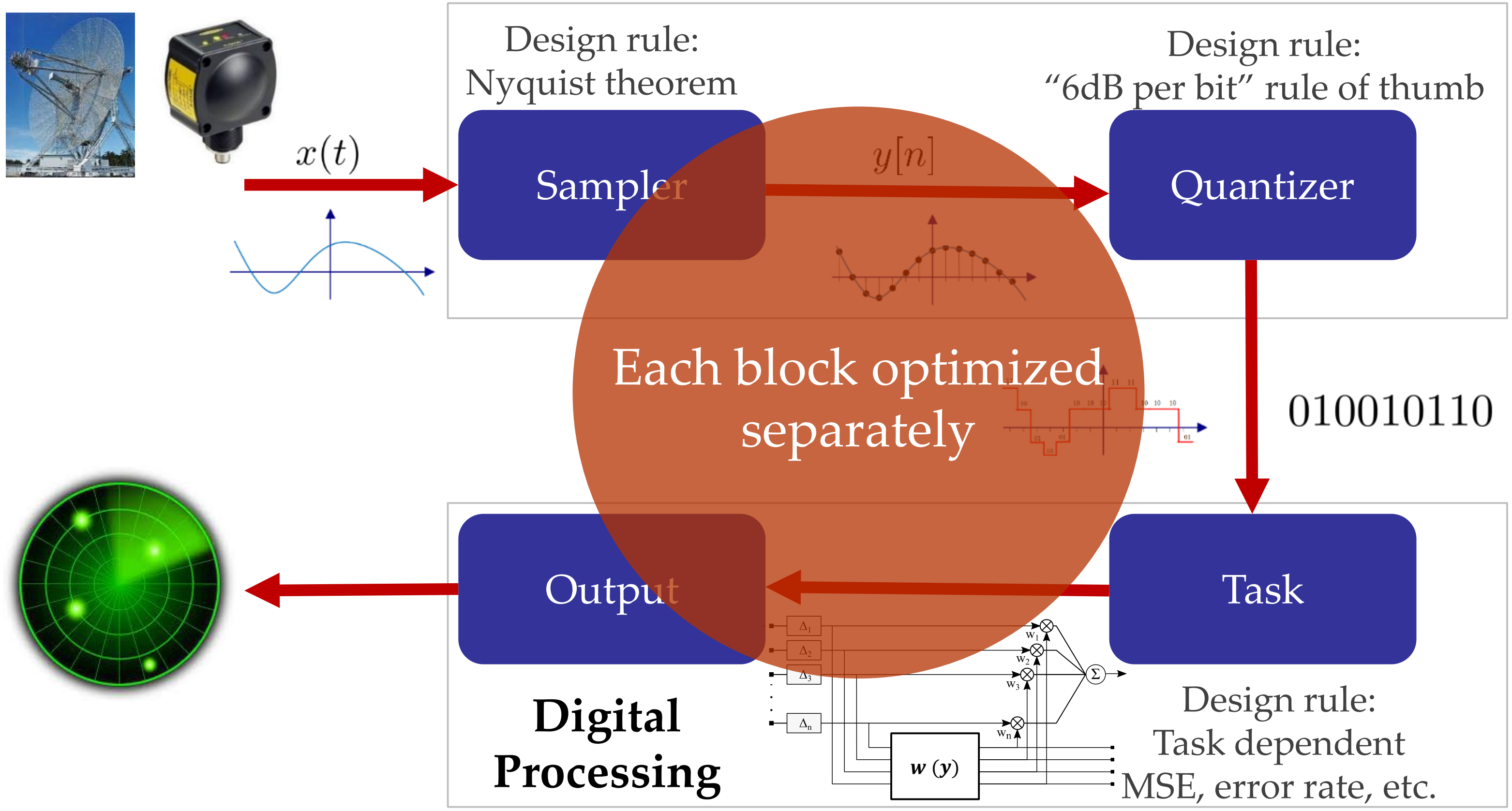


Digital world

→ $y[n]$ 010010110

- Signal processing
- Image denoising
- Compression…

Standard Acquisition Systems

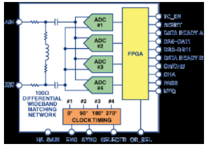


Limitations of Standard Systems

Large Bandwidth

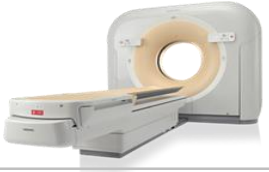
- High rate communications
- High resolution e.g. in radar and imaging

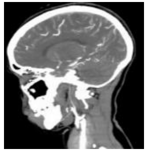
High rate samplers and quantizers



- **Large** and **expensive hardware-intensive** systems
- High-energy systems
- Large digital databases: **difficult to process, store and transmit**

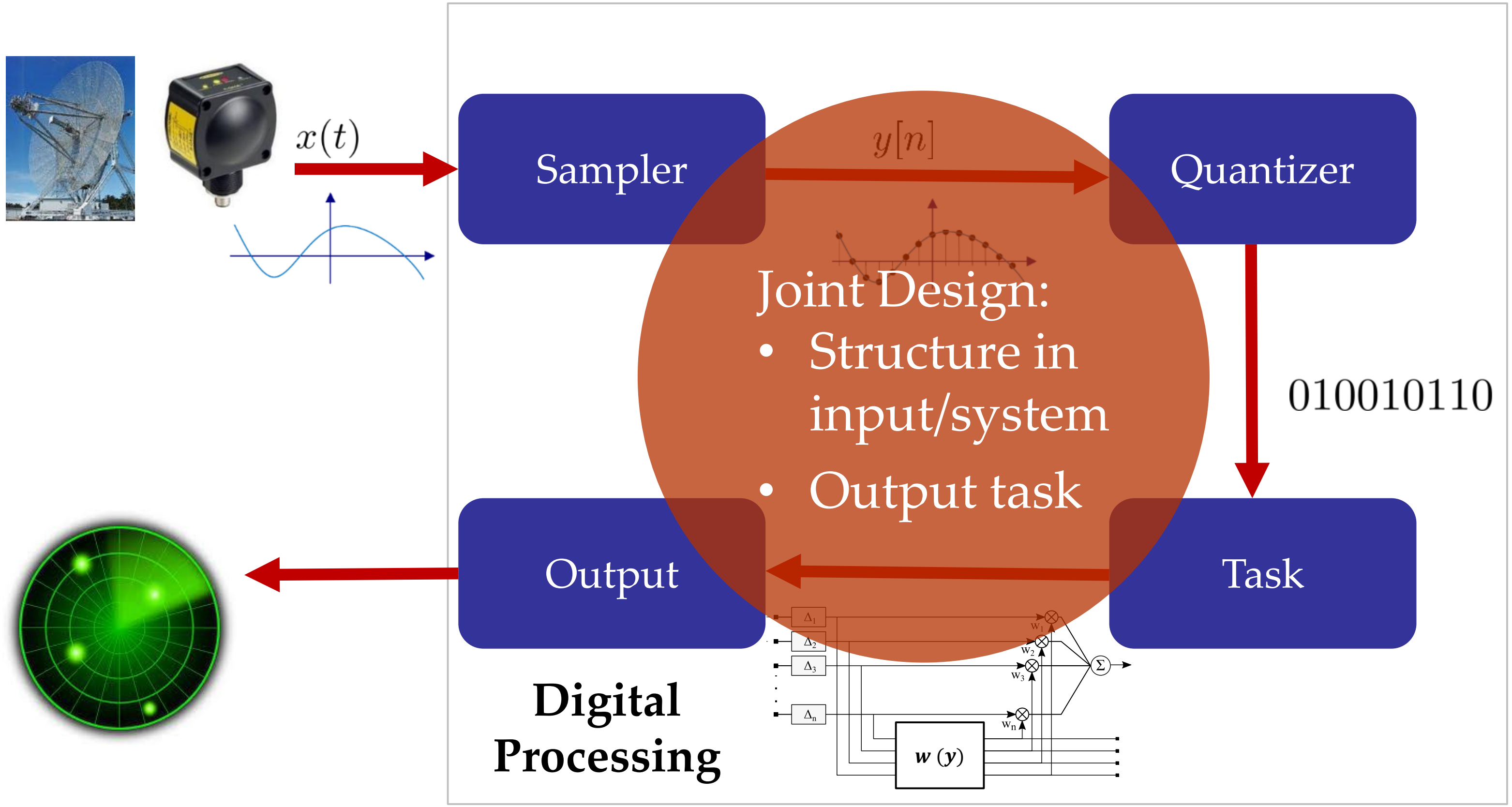
In medical imaging, high rates often translate into long scanning times or **high radiation dosages**





ADCs, the front end of all digital devices, lead to hardware, data and power bottlenecks

Task-Based Structured Acquisition



Model based, efficient, and interpretable data driven methods!

Advantages of Joint Design

Compact, portable devices with better imaging and detection quality

Joint radar and communication systems

Efficient wideband sensing

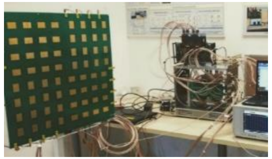
Compact, cheap and high resolution radar

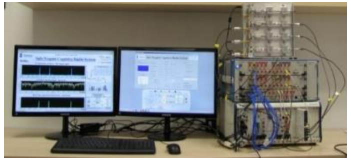
Efficient massive MIMO systems

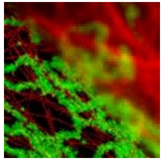
High performance Low-bit quantization

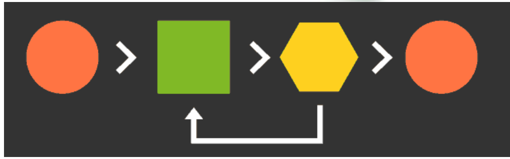
Super resolution microscopy and ultrasound

Interpretable, deep networks for communication, medical imaging, radar and more



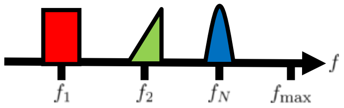


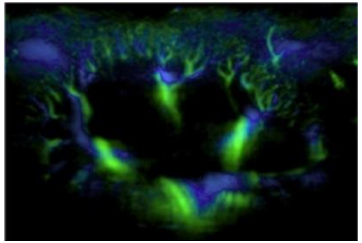


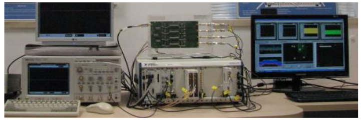


Talk Outline

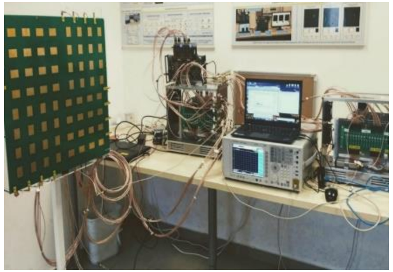
- Exploiting structure: From Sampling to Xampling
  - Sub-Nyquist ultrasound and radar
  - Wireless ultrasound



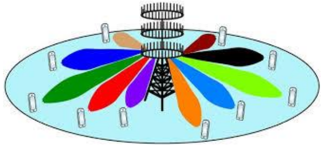


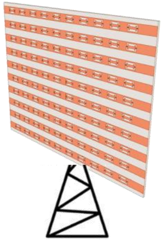


- Exploiting tasks: Task-based sampling
  - Power spectrum estimation
    - Cognitive radio
    - Super-resolution microscopy and US

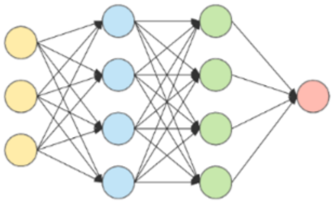


  - Task-based quantization
    - Efficient massive MIMO systems
    - Federated learning
    - Metasurface multiantenna systems
    - Joint radar-communication systems





- Exploiting models: Model-based deep learning



Part 1:

From Sampling to Xampling

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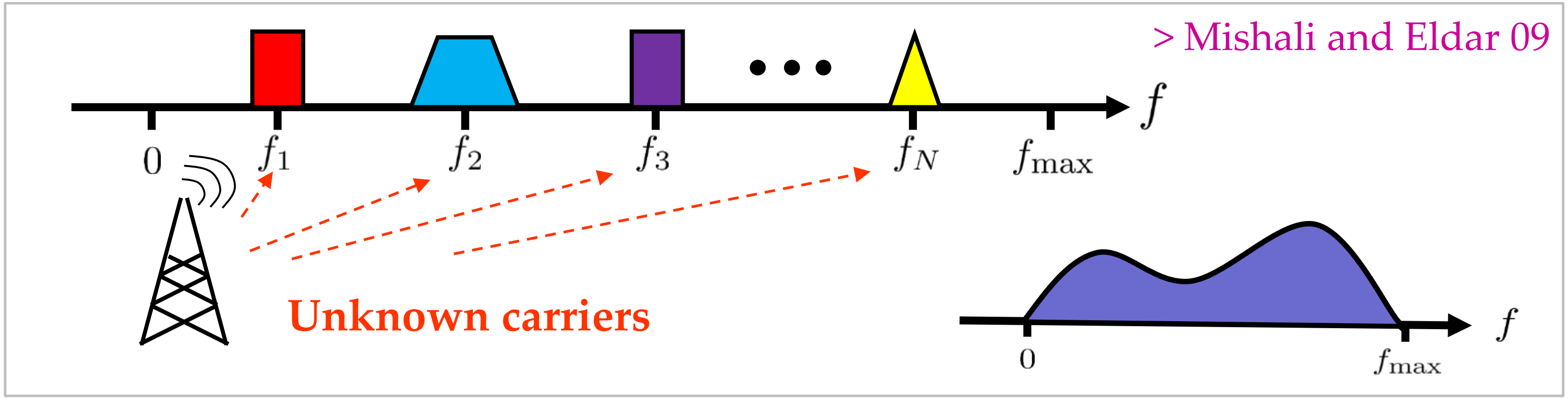
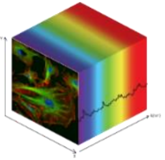
Multiple Frequency Bands

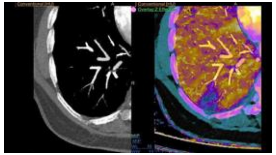
› Multiband Communication

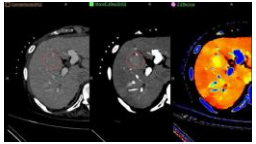


- Can be viewed as $f_{\max}-$ bandlimited
- But sampling at rate $\geq 2f_{\max}$ is a waste of resources
- For wideband applications Nyquist sampling may be infeasible

› Multispectral imaging, multispectral CT



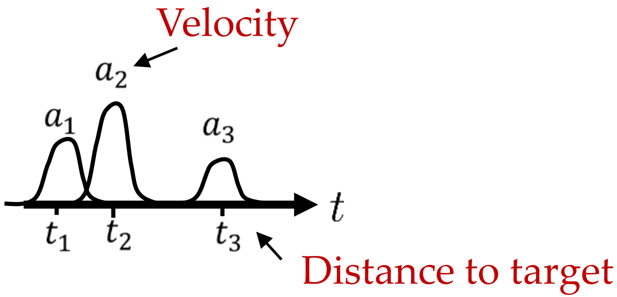




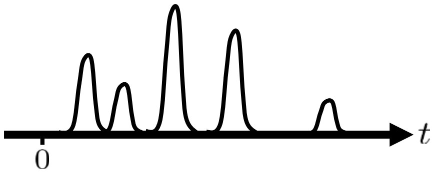
Streams of Pulses

Radar:

> Vetterli et. al, 02



Ultrasound:

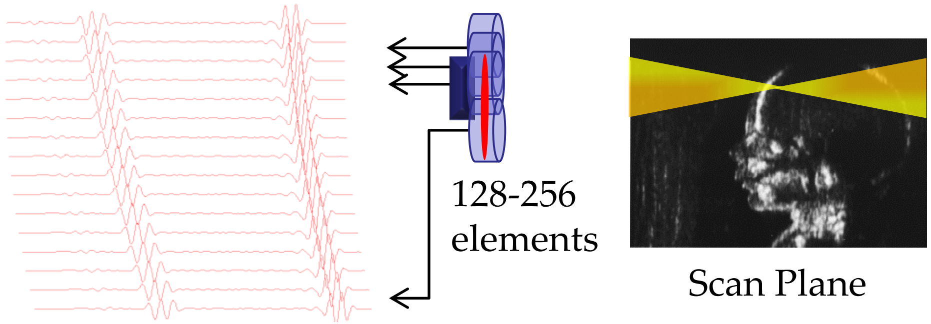


A sampler that takes advantage of the pulses' structure can use fewer samples and lead to higher resolution

Compressed Beamforming

> Chernyakova and Eldar 13-15

- SNR and resolution are increased by using an antenna array
- Beamforming is performed by introducing appropriate time shifts to the received signals



Focusing the received beam by applying nonlinear delays

$$\Phi(t;\theta)=\frac{1}{M}\sum_{m=1}^{M}\varphi_m\left(t-\frac{1}{2}\left(t-\sqrt{t^2-4(\delta_m/c)t\sin\theta+4(\delta_m/c)^2}\right)\right)$$

Requires high sampling and processing rates (lots of data…)

One image trace needs 128 samplers @20M, beamforming to 150 points, total of $6.3\text{x}10^6$ sums/frame!

Challenges

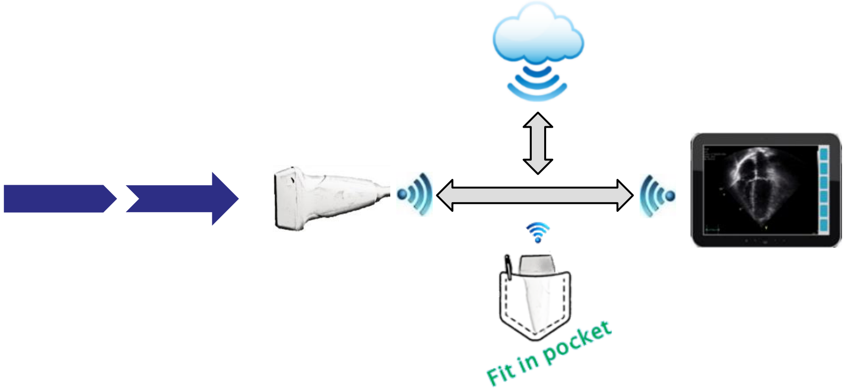
Can we…

- Reduce analog sampling rates of very noisy signals
- Perform nonlinear beamforming on sub-Nyquist samples, without interpolating to the high Nyquist-rate grid digitally

?

Yes, use Compressed Beamforming!

- Reduce US machine size at same resolution
- Increase frame rate
- Enable 3D imaging
- Enable remote wireless ultrasound



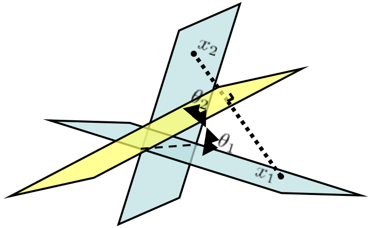
Union of Subspaces

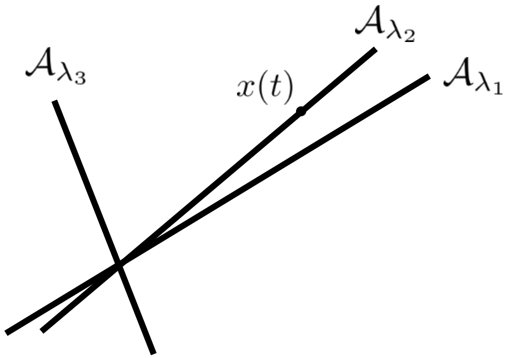
$$\mathcal{U} = \bigcup_{\lambda \in \Lambda} \mathcal{A}_\lambda$$

> Lu and Do 08, Mishali and Eldar 09

$x(t) \in \mathcal{A}_{\lambda^*}$ $\rightarrow \lambda^*$ is unknown a-priori

Each $\mathcal{A}_\lambda$ has low dimension





- Allows to keep low dimension in the problem model
- Low dimension translates to low sampling rate

Theorem

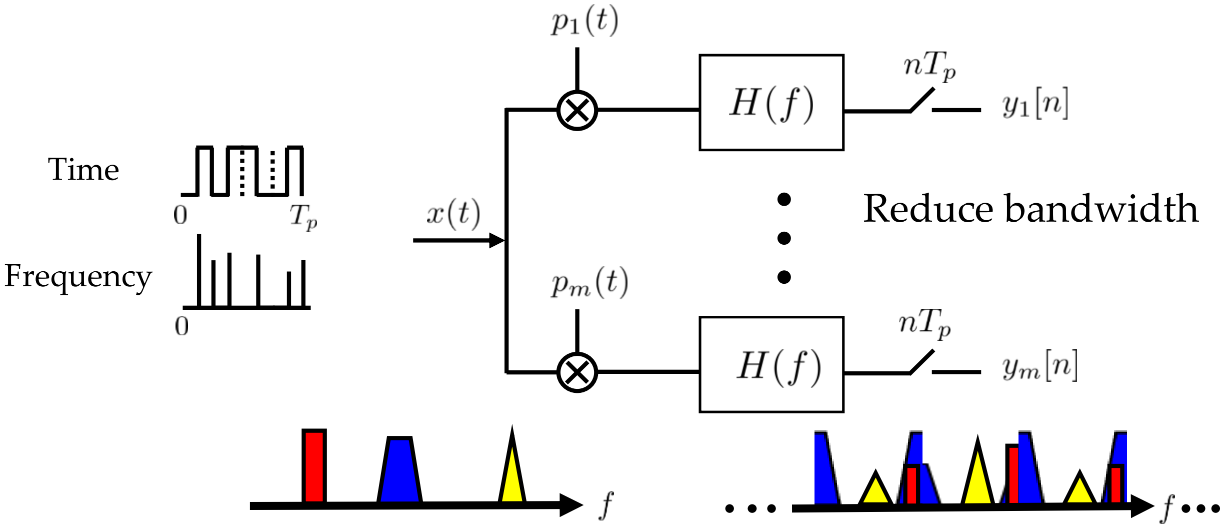
A sampling operator is invertible over a union of subspaces $\mathcal{U}$ if and only if it is invertible for every

$$\mathcal{A}_{\lambda,\gamma} = \mathcal{A}_\lambda + \mathcal{A}_\gamma = \{x | x = x_1 + x_2, \text{ where } x_1 \in \mathcal{A}_\lambda, x_2 \in \mathcal{A}_\gamma\}$$

Xampling Hardware

> Mishali and Eldar, 10-14

- Alias the data onto low dimensional space by mixing with periodic functions

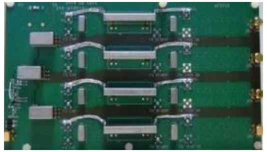


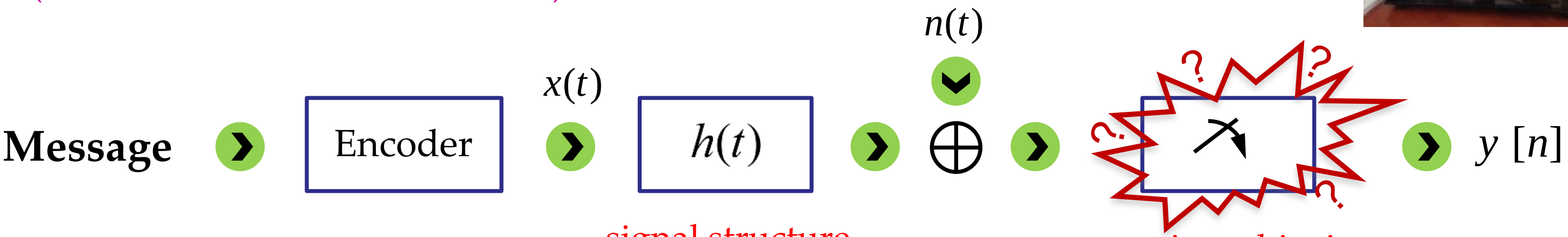
- Functions designed so that in digital we have a CS problem

Xampling Hardware

Sample at low rate using standard ADCs such that in digital we get a CS problem

- Low rate, low bandwidth, simple hardware and low computational cost
- Achieves the Cramer-Rao bound given a sub-Nyquist sampling rate (Ben-Haim, Michaeli, and Eldar 12)
- Minimizes the worst-case capacity loss for a wide class of signal models (Chen, Eldar and Goldsmith 13)





signal structure, captured by channel

capacity-achieving sub-Nyquist sampler

$$\min_{\text{sampler}} \max_{\text{states}} \text{CapLoss} \approx \frac{1}{2}\left\{\mathcal{H}(\beta) - \alpha\mathcal{H}\left(\frac{\beta}{\alpha}\right)\right\}$$

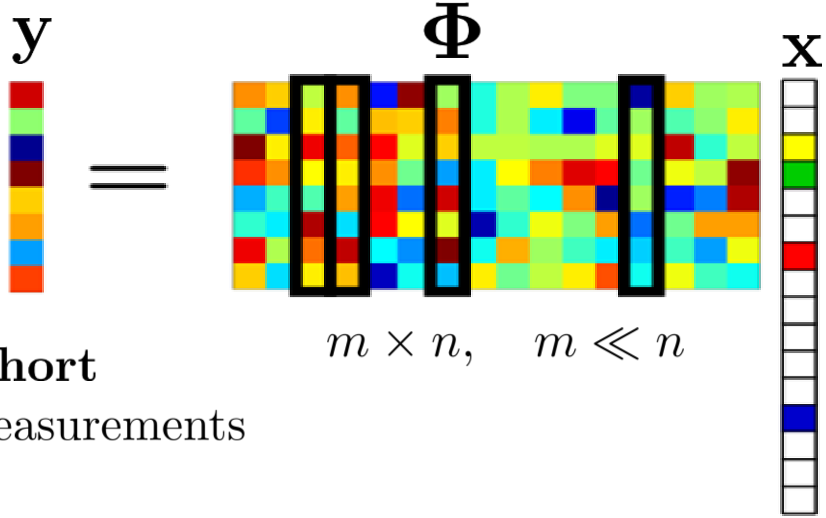
$$\mathcal{H}(\beta) = -\beta\log\beta - (1-\beta)\log(1-\beta)$$

binary entropy function

- α: undersampling factor
- β: sparsity ratio

Compressed Sensing

> Candes, Romberg, Tau 06, Donoho 06



$m \times n, \quad m \ll n$

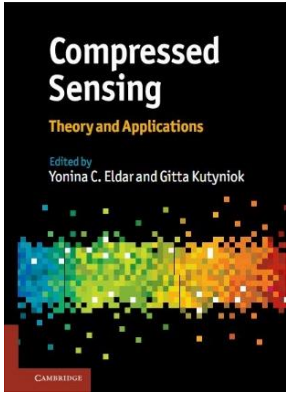
Short

$\approx 2K$ measurements

Long

K-sparse

(K nonzeros)

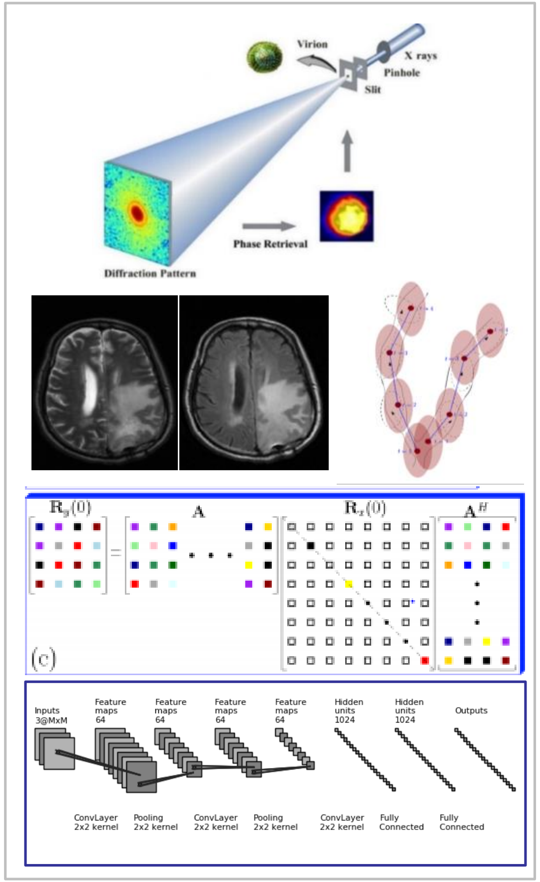


Main ideas:

- Sparse input vector with unknown support
- Sensing by sufficiently incoherent matrix (semi-random)
- Polynomial-time recovery algorithms from $K \log n$ measurements

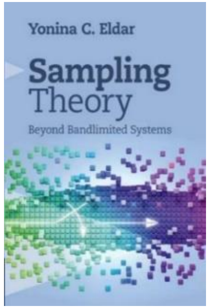
Compressed Sensing Extensions

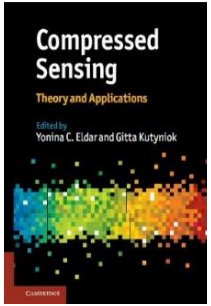
- Nonlinear sparse recovery (optics):
  - Phase retrieval
    (Shechtman et. al 11, 14, 15, Eldar and Mendelson 12, Ohlsson et. al 12)
  - Nonlinear compressed sensing
    (Beck and Eldar 12, Bahman et. al 11, Ohlsson et. al 13, Yang et. al 15)
- Reference based sparse recovery (MRI)
  (Weizman, Eldar and Ben Bashat 16)
- Sparsity with tracking (ultrasound) (Solomon et. al 18)
- Statistical sparsity
  (Pal and Vaidyanathan 14, Solomon et. al 18, Cohen and Eldar 18, Romero et. al 16)
- Deep learning (Gregor and LeCun 10, Mousavi and Baraniuk 17, Borgerding et. al 17, Aggarwal et. al 18, Bora et. al 17, Wu et. al 19)

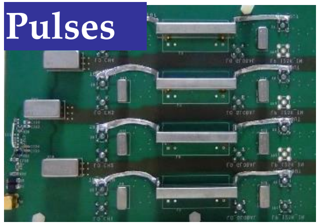


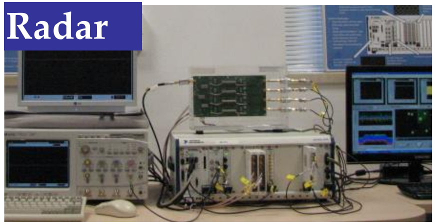
Xampling: Practical Compression + Sampling

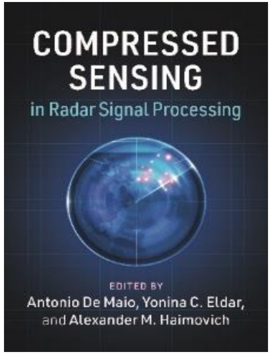
- Xampling: practical sub-Nyquist sampling and processing
- Many examples in which we reduce sampling rate by exploiting structure
- Low rate translates to lower radiation dosage, faster scanning, processing wideband signals, smaller devices and improved resolution

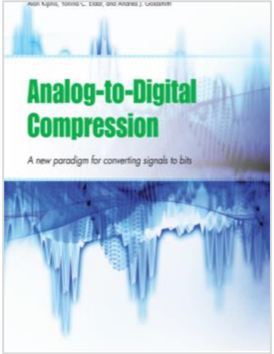


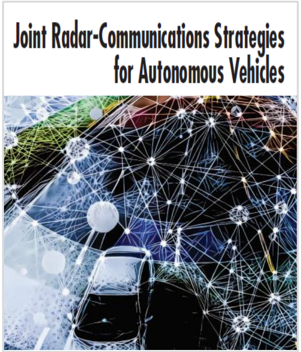




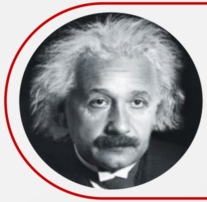








Applications



"In theory, theory and practice are the same. In practice, they are not."

Albert Einstein

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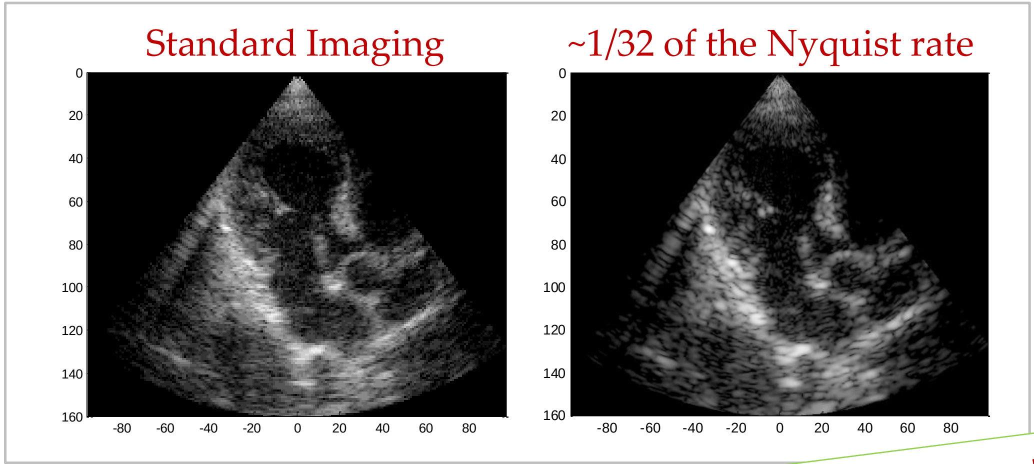
Sub-Nyquist Ultrasound Imaging

> Chernyakova and Eldar 13-15



4% Nyquist rate at every channel!

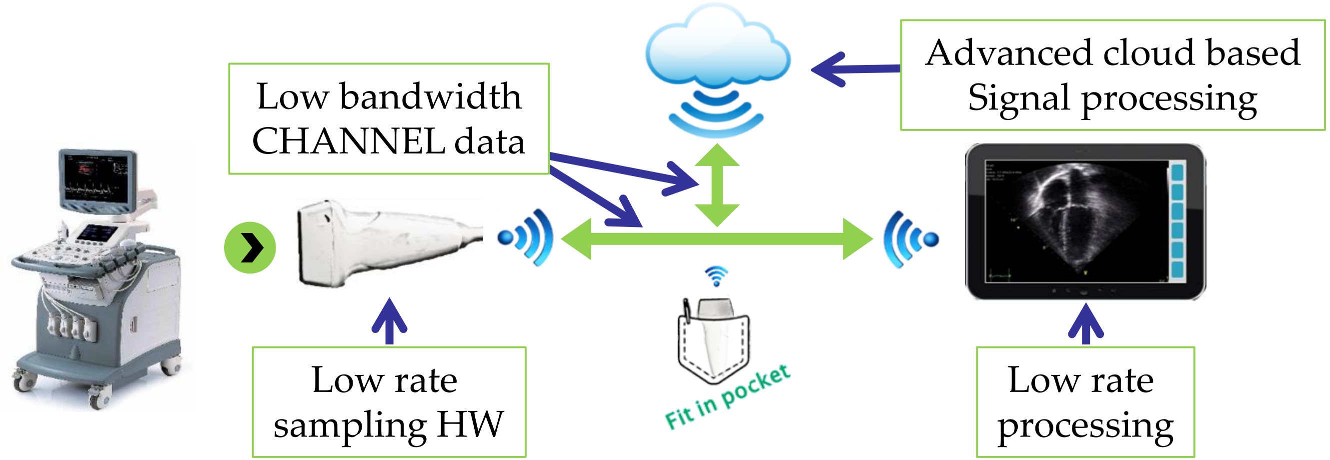
Low rate sampling enables:

- 3D imaging
- High frame rate for cardiac imaging
- Handheld wireless device: rural medicine, emergency imaging in the field/ambulance

Bring the Digital Revolution to Ultrasound, Anywhere

Xampling technology samples and processes ultrasound signals without loss of information at very low rates!

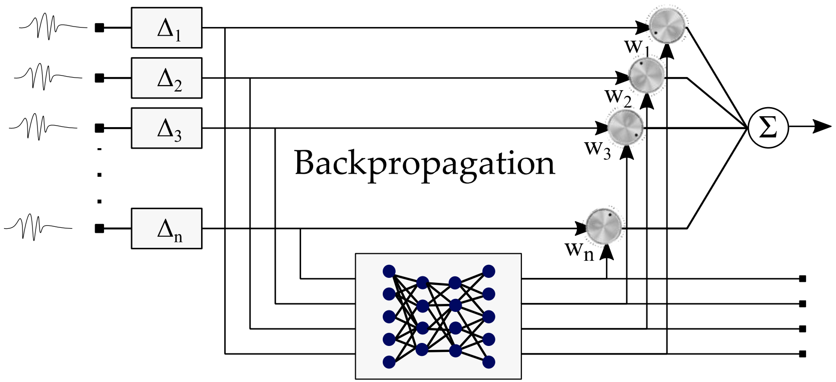
- Allows to integrate electronics into probe: wireless ultrasound
- Enabling an “open imager” – advanced signal processing and AI methods **on channel data** that can run on any platform
- Enabling remote health flexibility
- Super resolution methods



Demo Movie

Deep Adaptive Beamforming

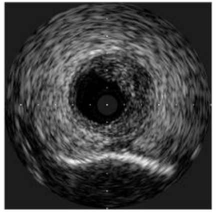
> Luijten et. al 19



PHILIPS

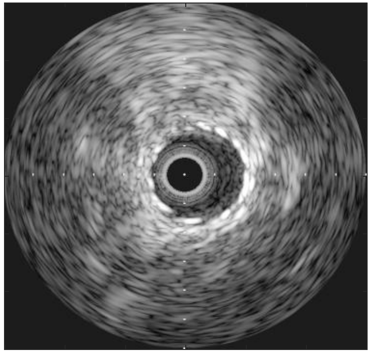
TU/e EINDHOVEN UNIVERSITY OF TECHNOLOGY

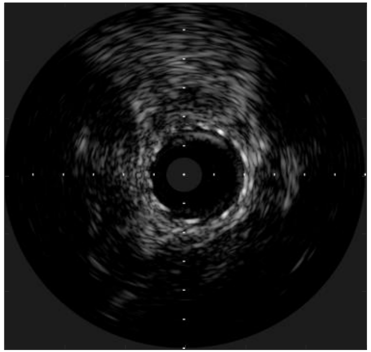
High-quality target (EBMV)



Model based: Weights determined by deep learning!

Delay-and-sum (standard)





Deep learning

Improved contrast and resolution

Channel Data Clinical Forum

Improve diagnostics from channel data!

- Ovarian cancer detection with MGH and MIT
- Tumor classification with NYU medical and Siemens
- Breast cancer detection with Beilinson
- Children cardiology with Shiba
- US for developing countries with Children's hospital and Brigham Women
- Detection of pleural diseases with Haemek
- Fetal anemia detection with Hillel Yaffe

Channel data!

Low rate sampling HW

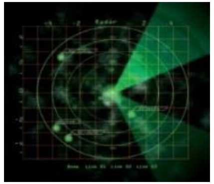
New clinical applications enabled by new acquisition strategy

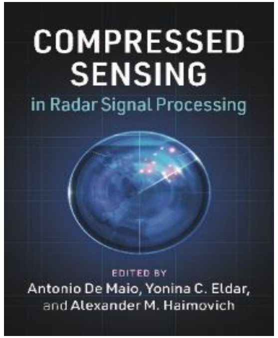
Radar/Time of Flight Imaging

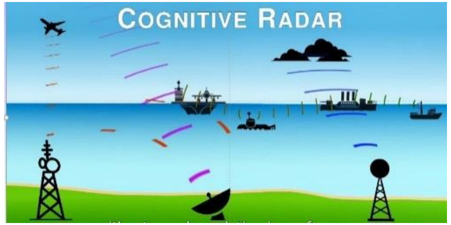
> Bar-Ilan and Eldar 14, Rossi et. al 14, Cohen and Eldar 18, Cohen et. al 18

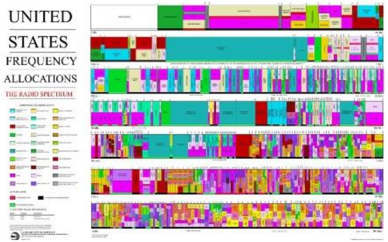
- Small, cheap radars with excellent resolution
- We can also reduce physical parameters:
  - Create a radar map in less time
  - Use fewer antenna elements
- Spectrum sharing between radar and communication over the same channel
- Free congested spectrum
- Fast frequency detection

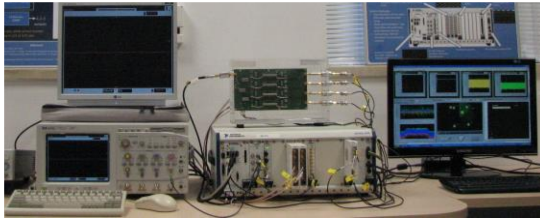




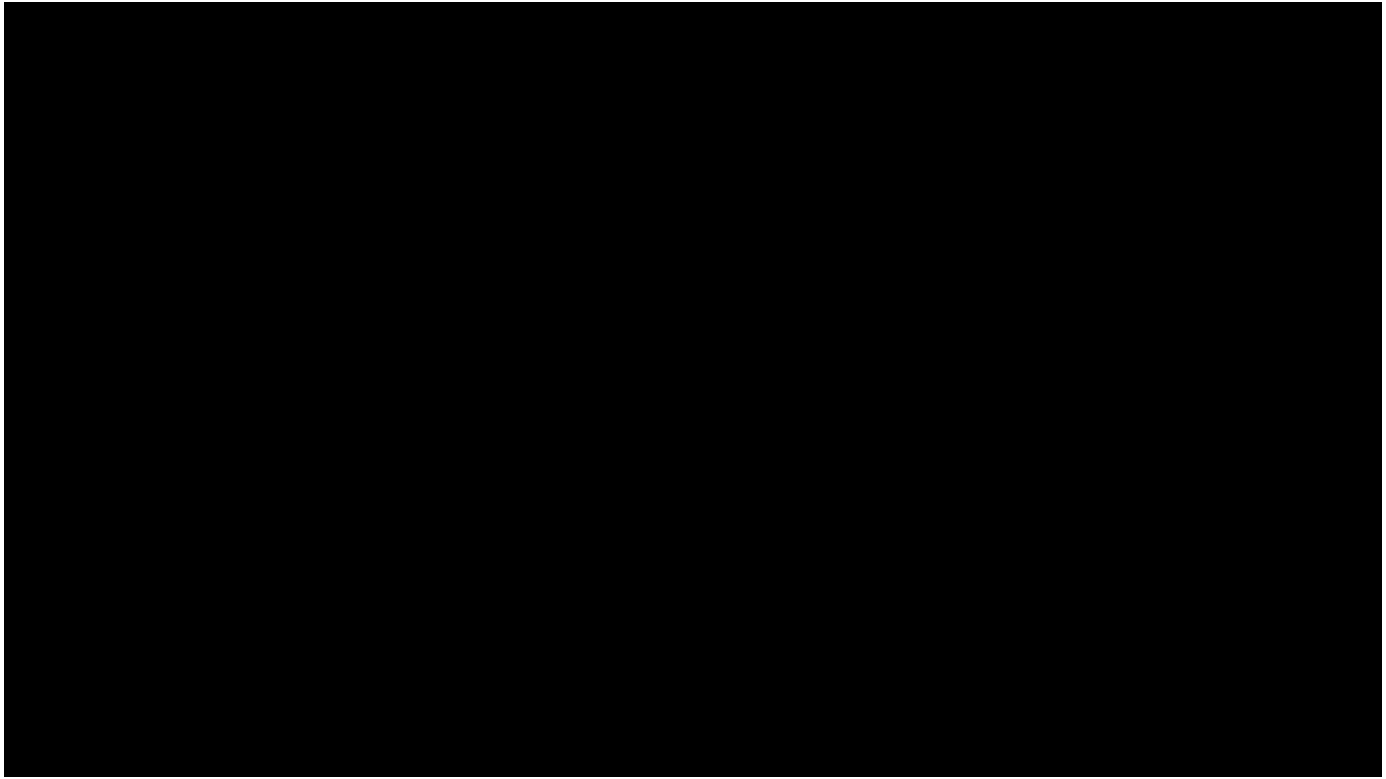


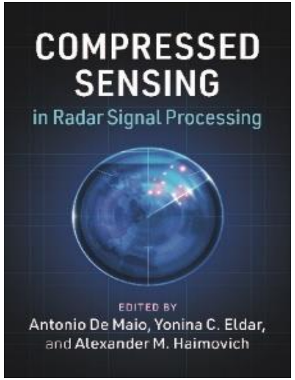






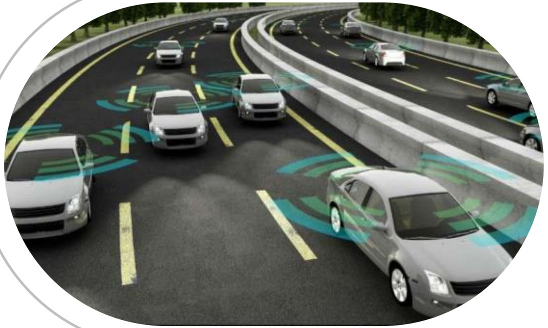
Sub-Nyquist and Cognitive Radar





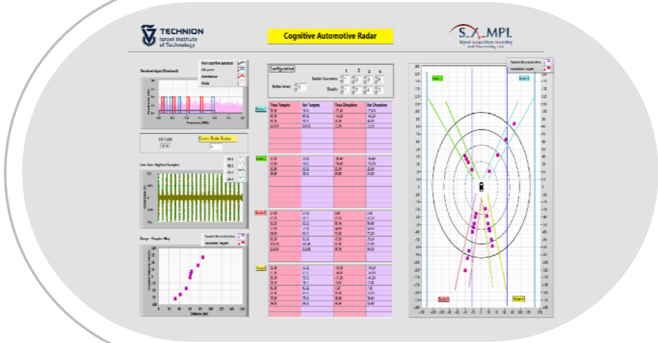
Cognitive Automotive Radar

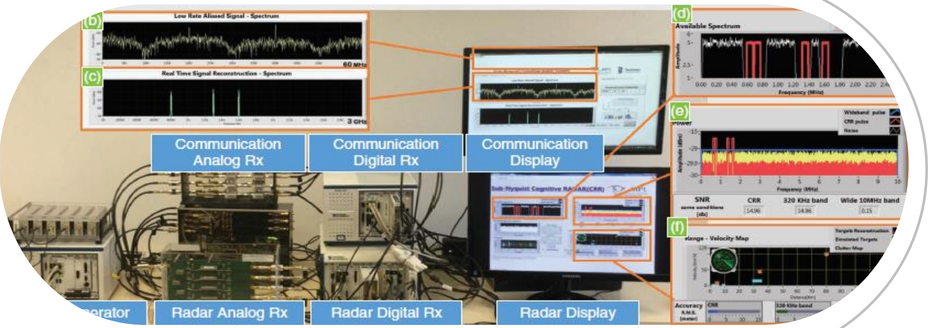
> Mulleti et. al 18-20



- In autonomous systems the number of vehicles (radars) vary over time
- Radars require to share bandwidth without interference
- Our cognitive system divides the bandwidth into multiple narrow subbands adaptively
- Based on desired no. of radars the subbands are assigned to each radar

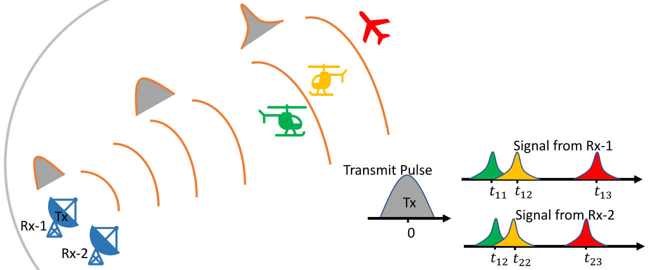
Sub-Nyquist sampling with robust reconstruction is achieved!





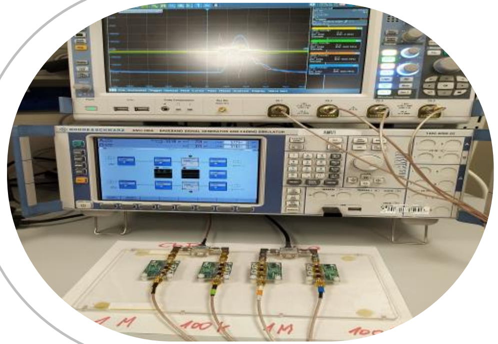
Radar With Unknown Pulse Shape

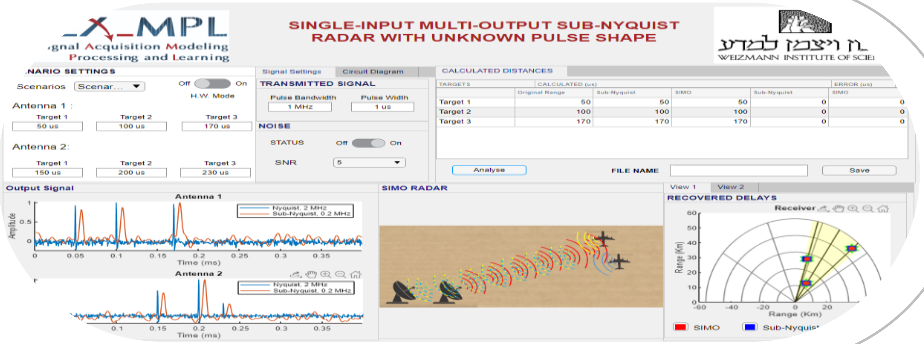
> Mulleti et. al 20



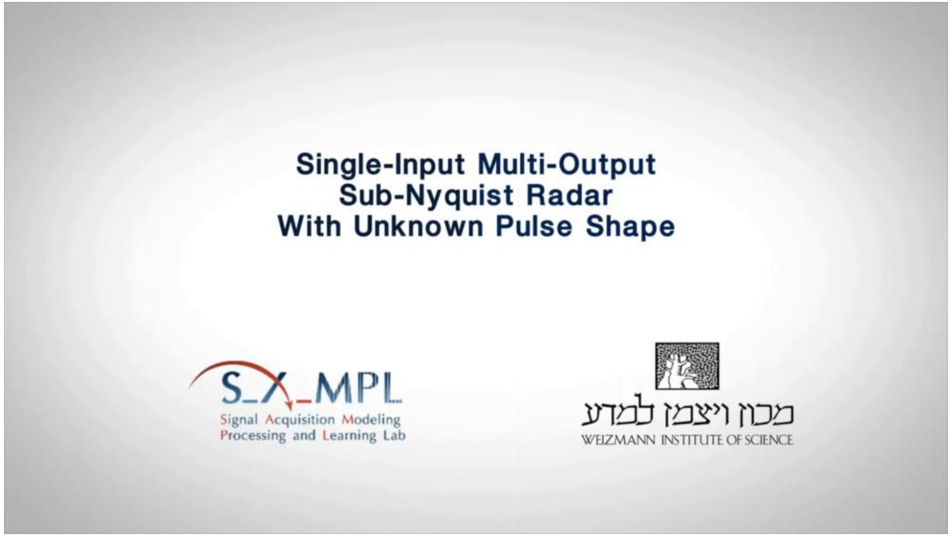
- In practice the pulse shape can be distorted and unknown
- We propose the use of multiple receivers (at least 2) to recover the targets and pulse
- Each Rx operates at a sub-Nyquist rate

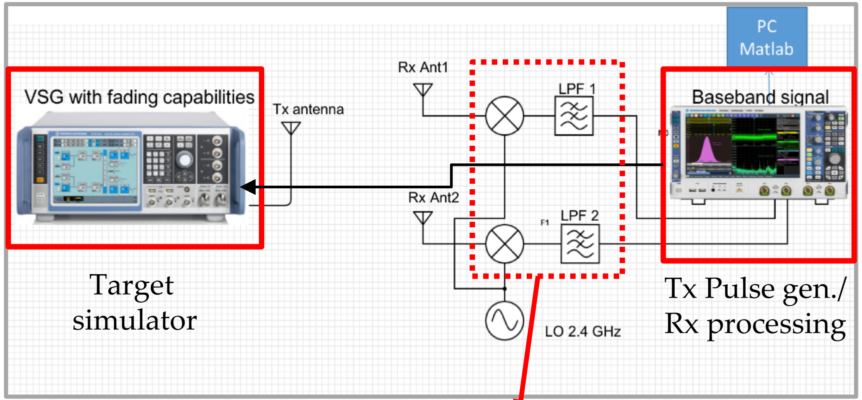
Signal recovery from samples at 10 times lower than Nyquist

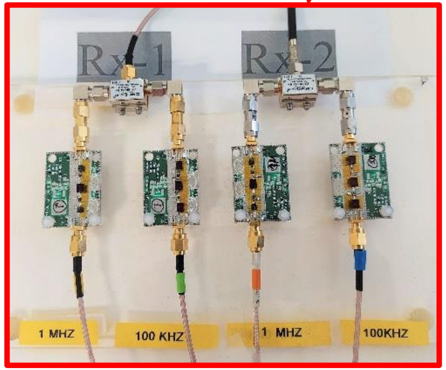




Blind SIMO Sub-Nyquist Radar





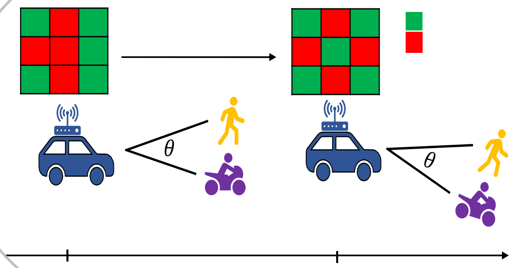


Lowpass filters for Rx

Allows for low power, low BW radar detection in complicated settings like automotive radar

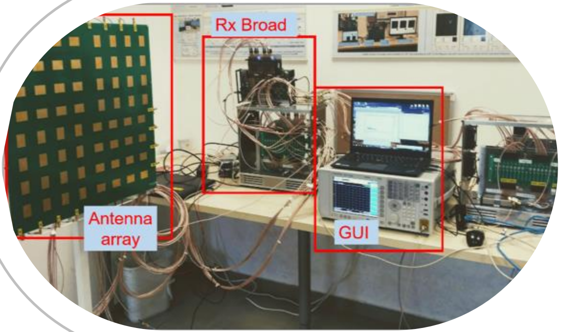
Deep-Sparse Antenna Array

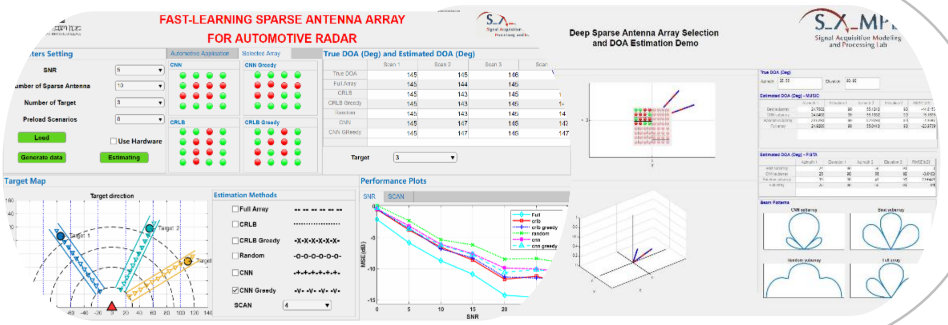
> Mulleti et. al 19-20



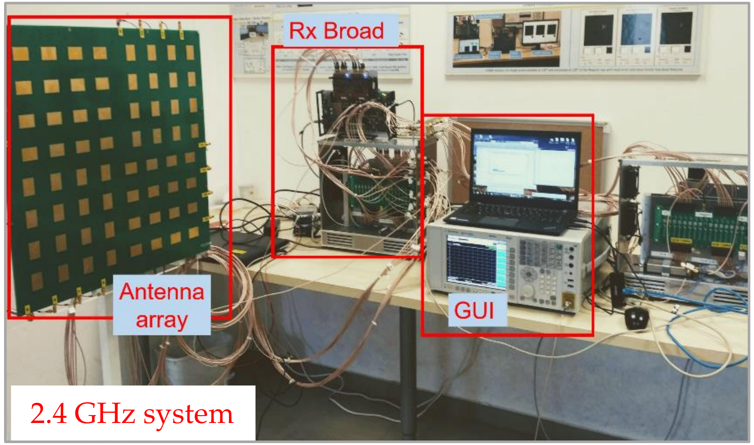
- High-res DOA ❯ Large array ❯ High-cost, power
- We propose NN-based sparse subarray selection
- The method is cognitive and adapts according to the current target scene
- The method is scalable and performs better than a non-adaptive random selection method

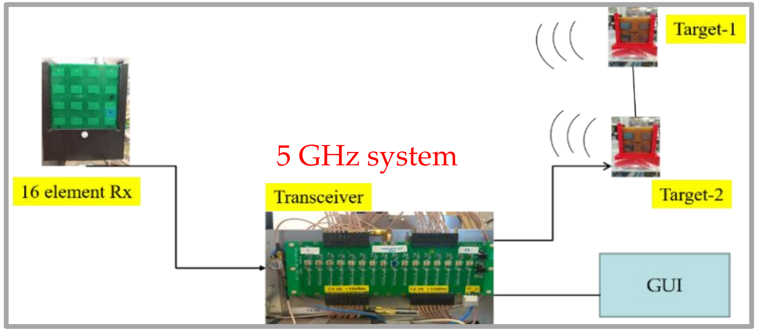
Sparse arrays are crucial in automotive radar to save battery!





Deep-Sparse Antenna Selection

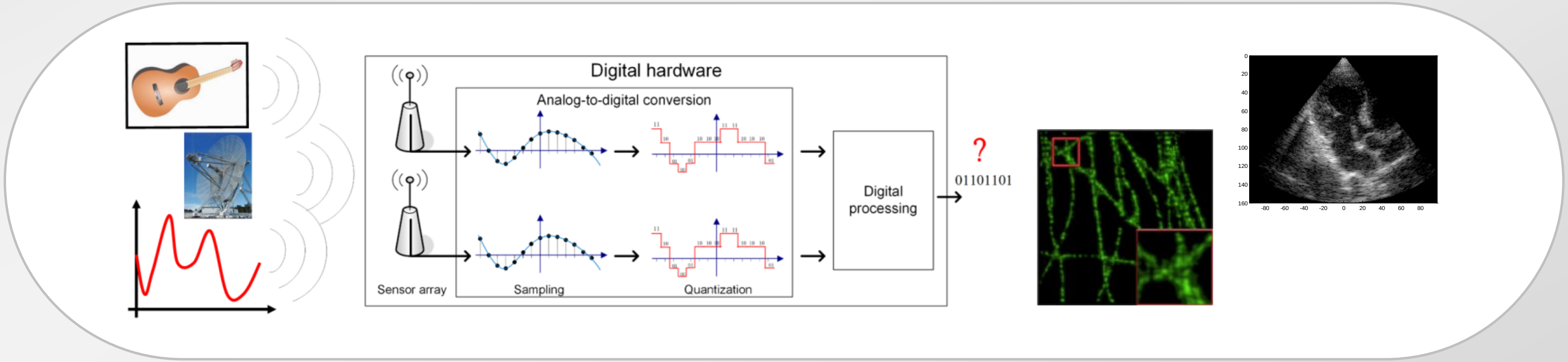






Part 2:

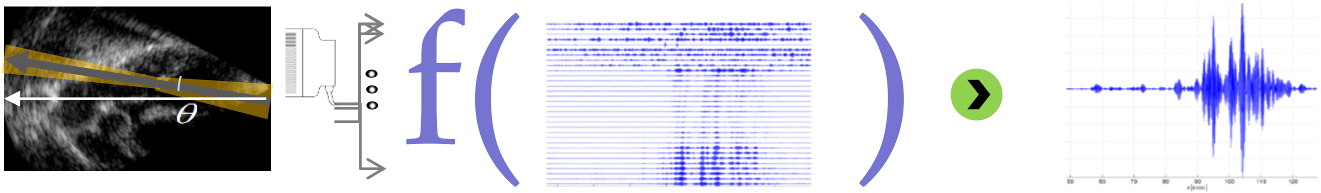
Task-Based Sampling

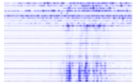


Task-Based Sub-Nyquist Sampling

Can we reduce sampling rates for signals without structure?

Consider the case where we don't actually need the signal, but rather some function of it

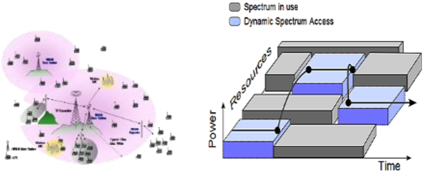


Easier than  ?

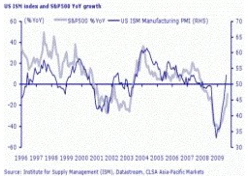
- Signal statistics: Power spectrum estimation > with Geert Leus and Deborah Cohen
- Quantized version of the signal > with Alon Kipnis, Andrea Goldsmith, and Tsachy Weissman
- Task-based quantization in communication > with Nir Shlezinger and Miguel Rodrigues
- Compressed beamforming > with Tanya Chernyakova and Regev Cohen

Power Spectrum Reconstruction

- Often the required information can be extracted from the covariance rather than the signal itself:
  - Support detection
  - Statistical analysis
  - Array processing (e.g. DOA)
  - Brightness image



Cognitive Radios



Financial time series analysis

What is the minimal sampling rate to estimate the signal covariance of a wide-sense stationary ergodic signal?

- Previous work studied specific samplers in the asymptotic regime:
  - Vaidyanathan 11: coprime sparse samplers with arbitrarily low rate
  - Tarczynski 07, Davies 11, Leus 12: multicoset samples with arbitrarily low rate

For covariance estimation substantial rate reduction is possible!

Covariance Estimation

> Cohen, Eldar and Leus 15

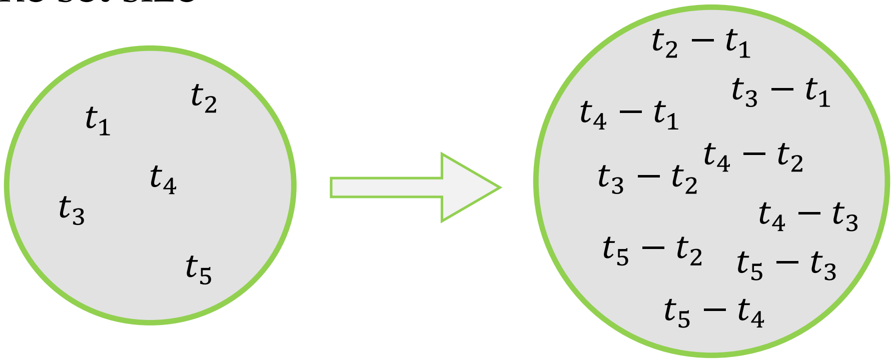
- Let $x(t)$ be a wide-sense stationary ergodic signal
- We sample $x(t)$ with a stable sampling set at times $\tilde{R} = \{t_i\}_{i \in \mathbb{Z}}$
- We want to estimate $r_x(\tau) = \mathbb{E}[x(t)\mathrm{x}(t-\tau)]$

What is the minimal sampling rate to recover $\boldsymbol{r_x(\tau)}$?

Sub-Nyquist sampling is possible even for finite rates!

Intuition:

- The covariance $r_x(\tau)$ is a function of the time lags $\tau = t_i - t_j$
- To recover $r_x(\tau)$, we only need the difference set which can grow quadratically in the set size



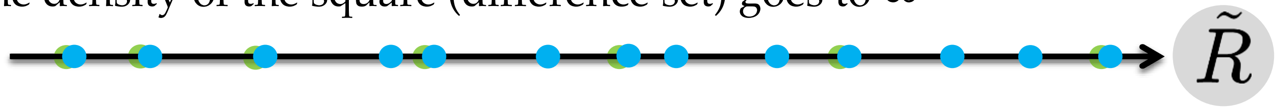
Sampling set $\tilde{R} = \{t_i\}_{i \in \mathbb{Z}}$

Difference set $R = \{t_i - t_j\}_{i,j \in \mathbb{Z}}$

Difference Set Density

It is possible to create sampling sets with Beurling density 0 for which the difference set has Beurling density ∞!

- The density of the set should go to 0 slower than the square root
- There should be enough distinct differences so that the size of the difference set grows like the square of the size of the sampling set
  - The density of the square (difference set) goes to ∞



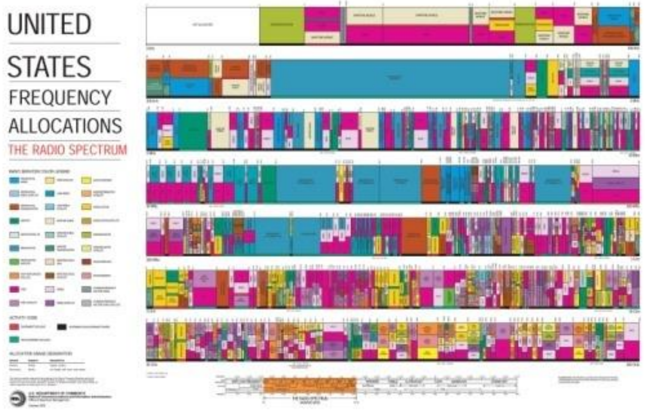
Theorem

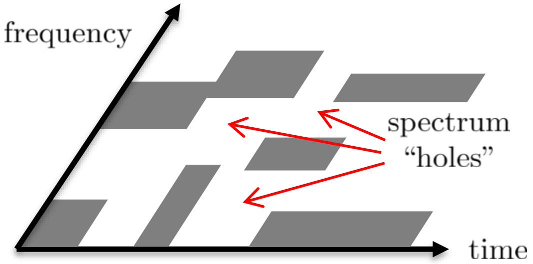
Let $\tilde{R} = \{t_i\}_{i\in\mathbb{Z}}$, be a sampling set with lower Beurling density $D^-(\tilde{R}) = 0$, so that the set of differences between two sets of size p and q is of the order of pq. Let $R = \{t_i - t_j\}, \forall t_i > t_j \in \tilde{R}$ be the associated difference set. If $\lim_{r\to\infty} \frac{d_{\tilde{R}}(r)}{\sqrt{r}} = \infty$, then, $D^-(R) = \infty$

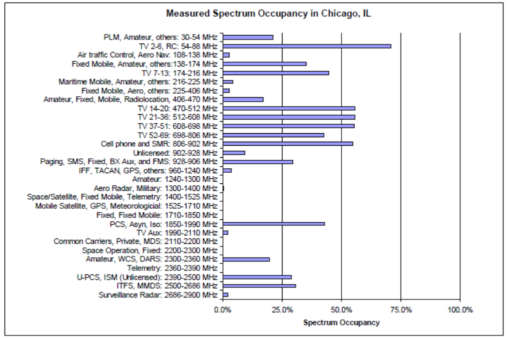
Cognitive Radio

- Cognitive radio mobiles utilize unused spectrum "holes"
- Need to identify the signal support at low rates

Federal Communications Commission (FCC) frequency allocation



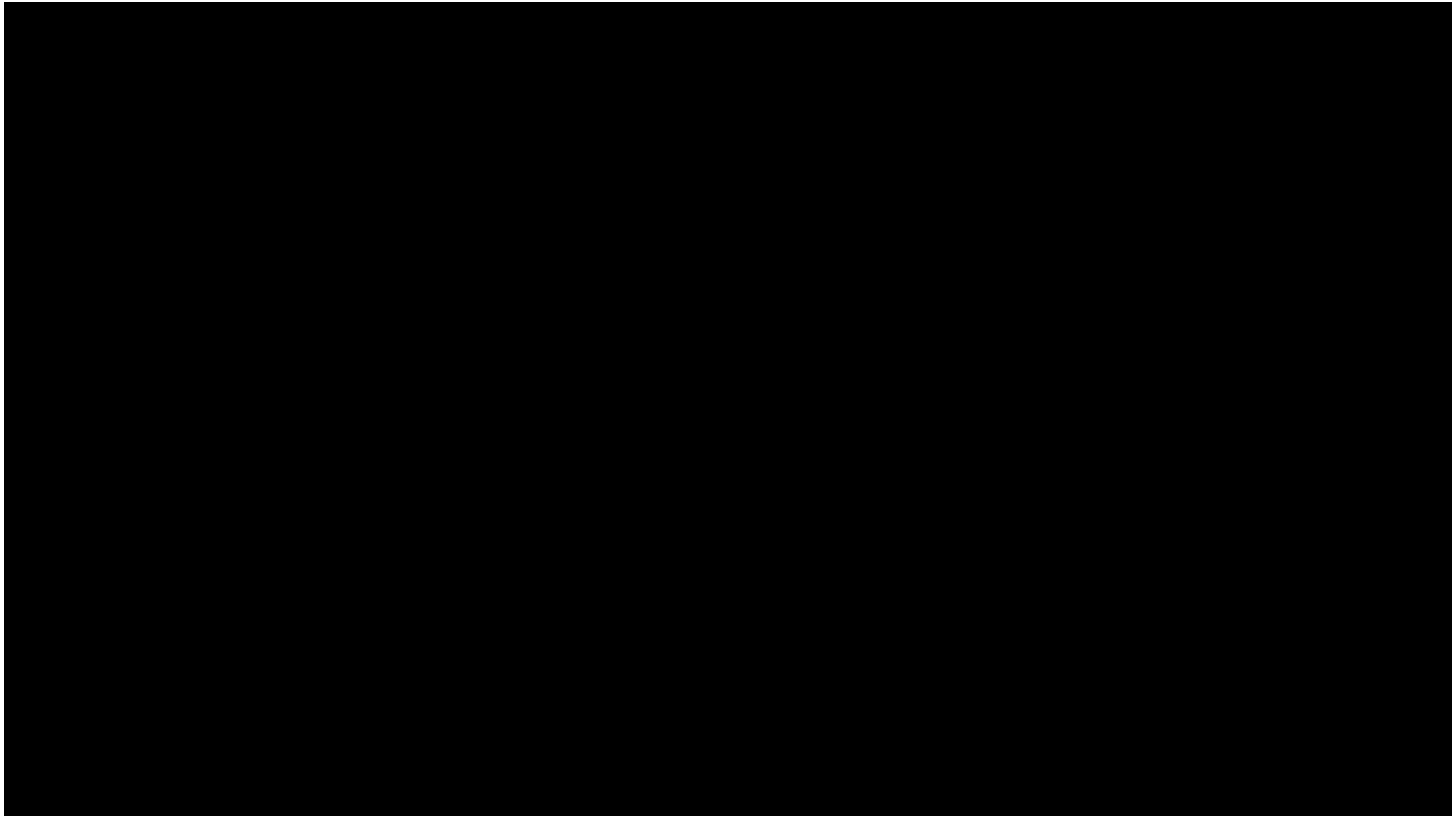


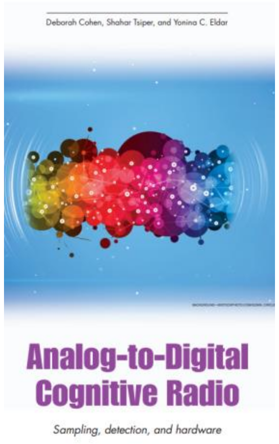


Shared Spectrum Company (SSC) – 16-18 Nov 2005

Licensed spectrum highly underused: E.g. TV white space, guard bands and more

Sub-Nyquist Cognitive Radio

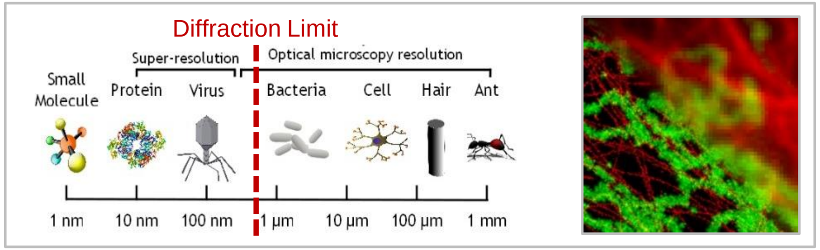




Super Resolution Microscopy

- Abbe's diffraction limit in optical imaging:

$$DL = \frac{\lambda}{2NA}$$

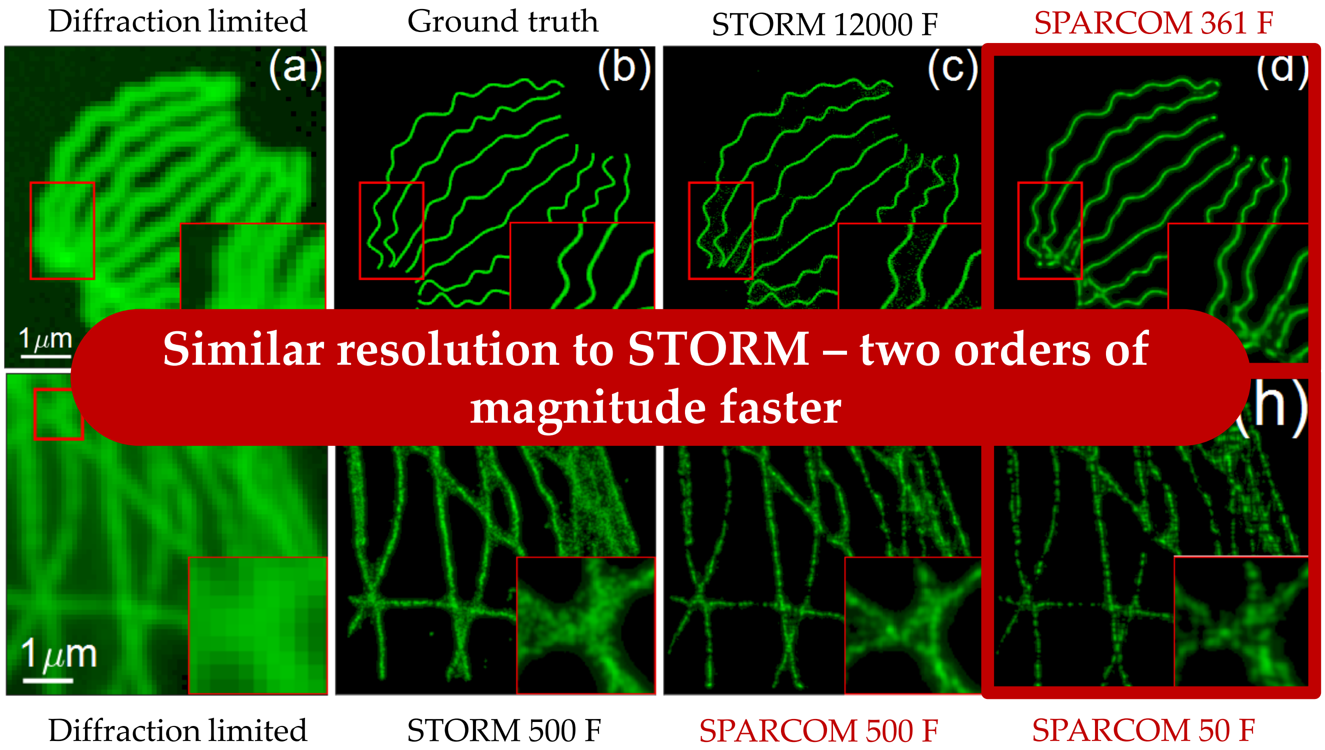


- Noble prize 2014: super resolution using optical fluorescence microscopy (Betzig, Hell, Moerner)
- New measurement process – control fluorescence of individual molecules
- Image the same area multiple times – only a few point-emitters each time
- Spatial resolution of ~20nm
- Limited temporal resolution! > 10000 frames to collect all molecules

Can we get both high temporal resolution and high spatial resolution?

SPARCOM: Super Resolution Correlation Microscopy

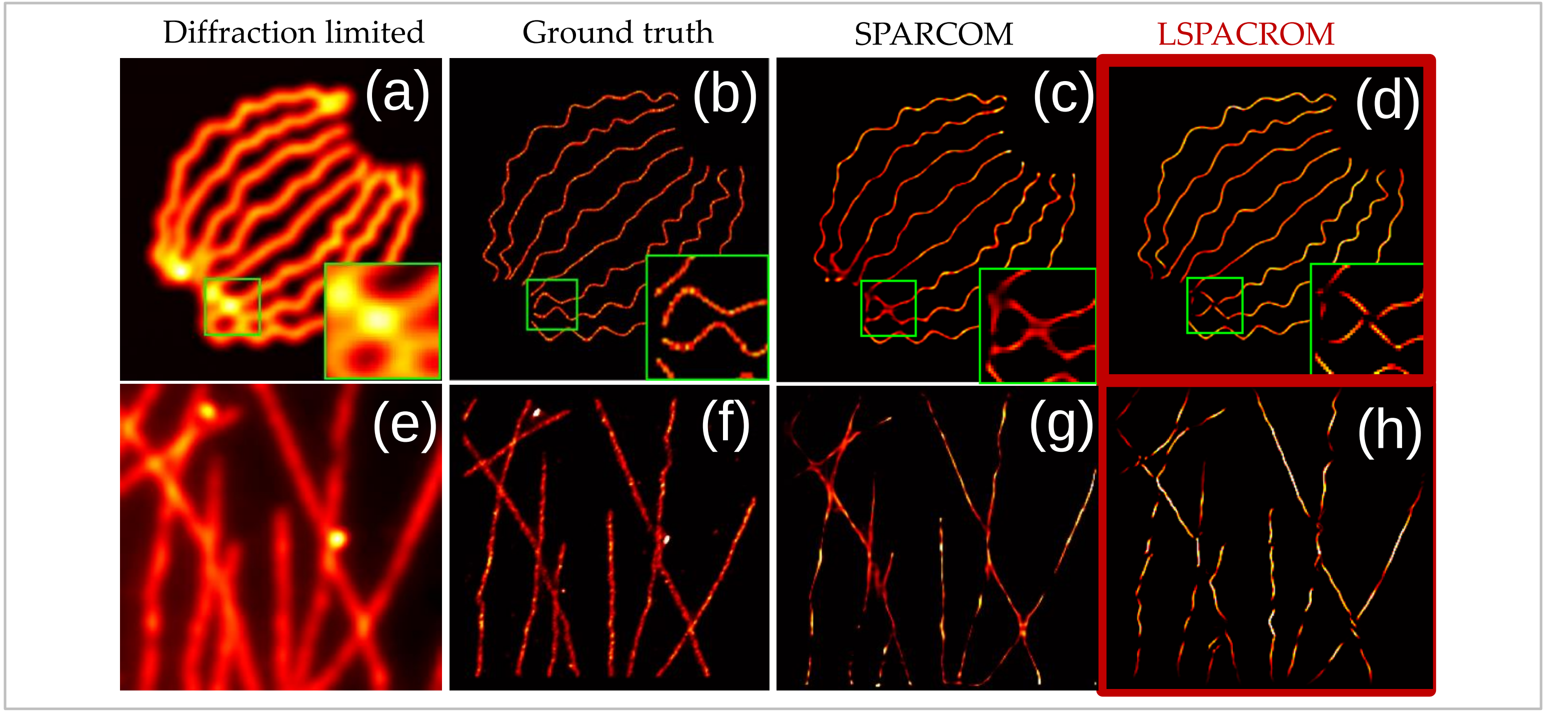
> Solomon et. al 18



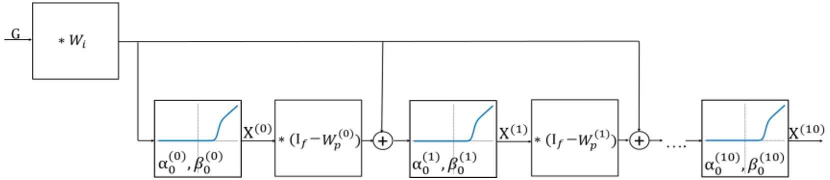
Data from: http://bigwww.epfl.ch/smlm/
Super-resolution microscopy web site developed by Prof. Michael Unser's group at EPFL

LSPARCOM: Learned SPARCOM

> Dardikman-Yoffe and Eldar, 20



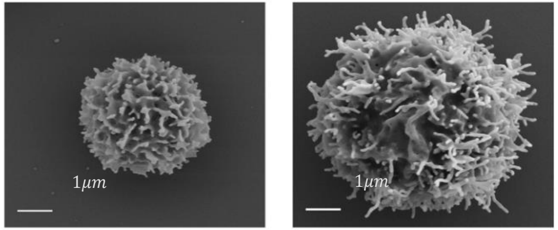
- Performance equivalent to SPARCOM, but with no prior knowledge regarding PSF or parameter selection
- 10 × improved convergence rate



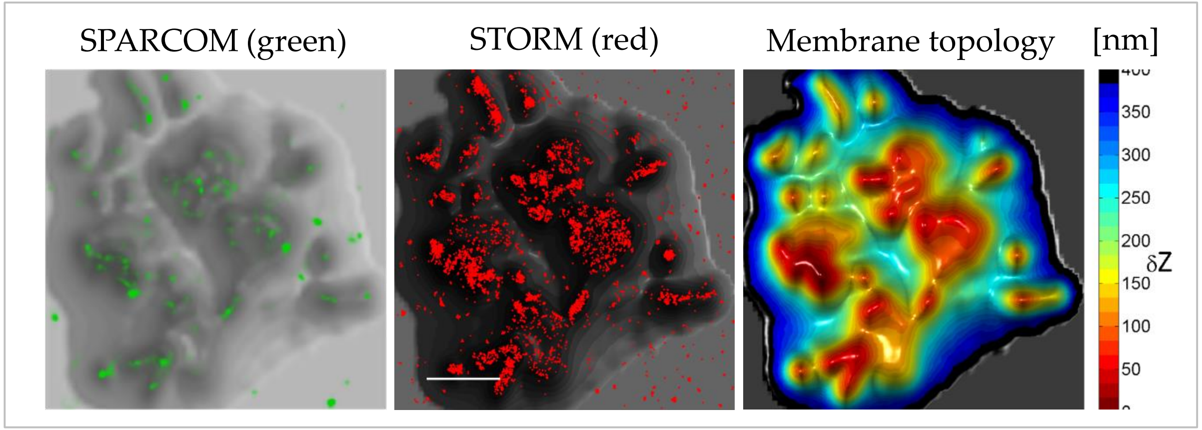
Super-resolution of T-cell Receptors

> Collaboration with the group of Prof. Haran from Weizmann

- Immune response of T-cells involves T-cell receptor (TCR) molecules
- TCRs are clustered inside the microvilli
- STORM experiment with 30000 exposures
- SPARCOM performs reliable recovery with **100 times shorter acquisition period**



May lead to live cell inspection of TCR arrangement

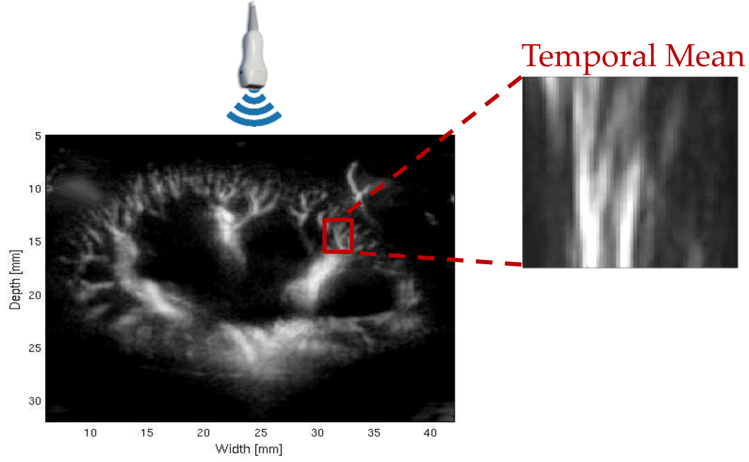


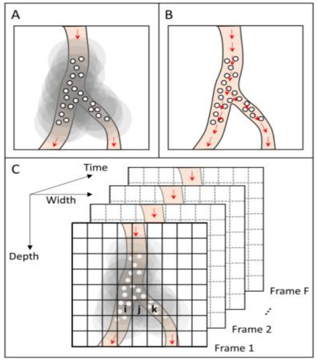
Super Resolution Contrast Enhanced Ultrasound

> Bar Zion et. al 18

Bolus **injection** of micro-bubbles into the blood stream → **Acquisition** of consecutive frames → **Sub-wavelength image**

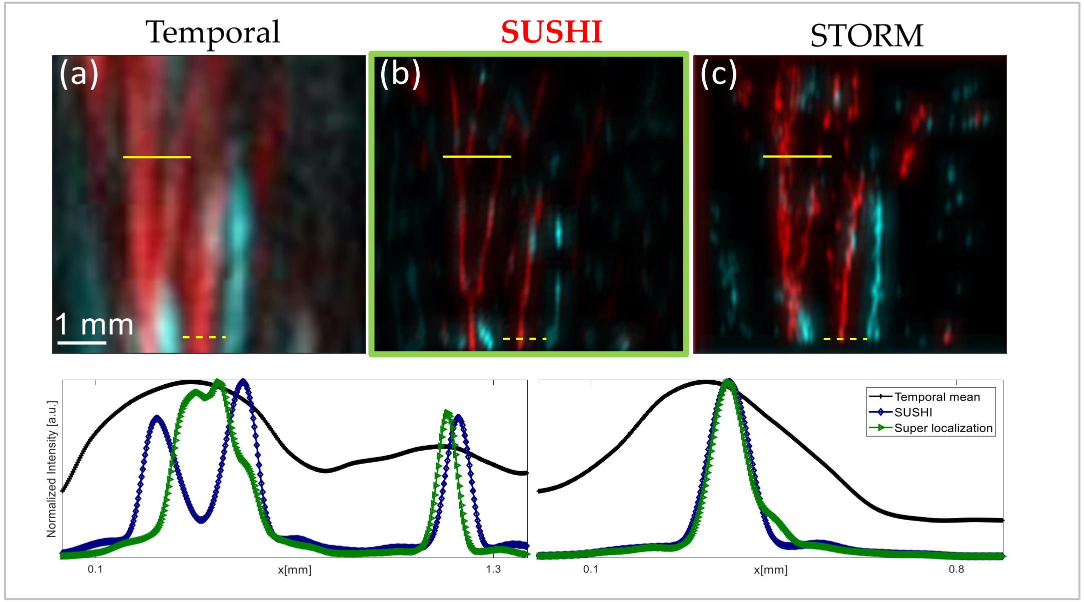
Micro-bubbles act as point emitters in the bloodstream





SUSHI: Sparsity-Based Ultrasound Super-resolution Hemodynamic Imaging

- Super-resolution imaging using CEUS in real-time
- Applications: Relapse detection & treatment monitoring in Crohn's disease, breast-cancer screening
- Clinical evaluation: Drs. Anat Ilivitzki (Crohn), Ahuva Grubstein and Yael Rapson (breast cancer)



RABIN MEDICAL CENTER
BEILINSON • HASHARON

RAMBAM

Super Resolution Ultrasound for Breast Lesions

> Collaboration with Drs. Ahuva Grubstein, Yael Rapson, and Dror Suhami

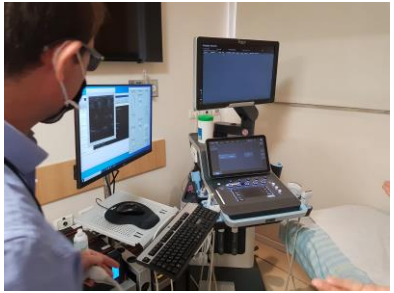
- Many imaging results are indeterminate requiring biopsy for pathologic confirmation
- Problems: emotional stress, risk of complications and additional time and cost
- Improved ultrasound imaging methods can provide advantages in screening and diagnosis

Scanning with our methods:

RABIN MEDICAL CENTER
BEILINSON • HASHARON

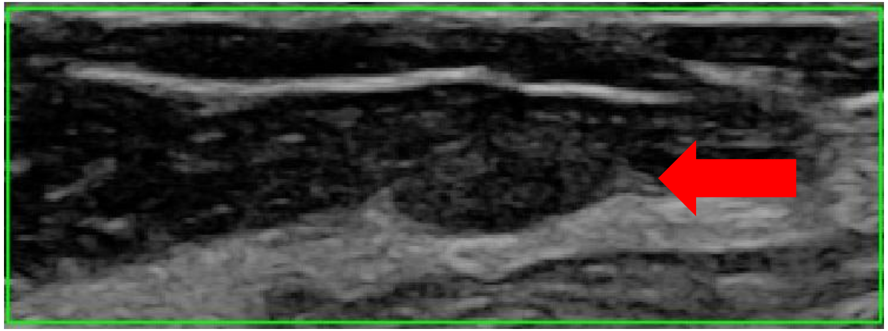
- One week of scans took place at Beilinson hospital
- A total of 21 patients between the ages of 30-70 participated
- 4 patients with malignant lesions and 17 patients with benign lesions
- Advanced sparsity based deep learning methods were applied to the data to get super resolved images at real time (< 1 min)



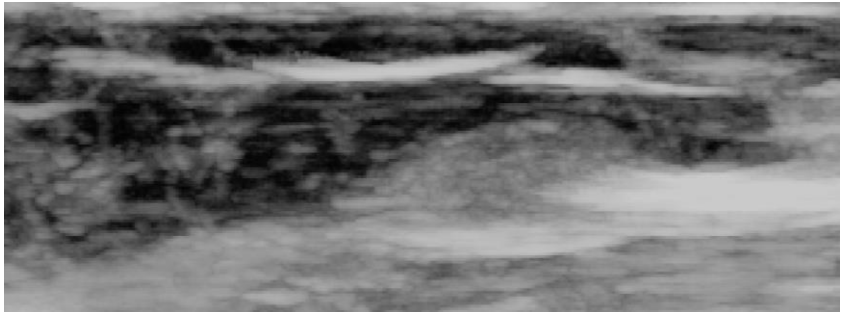


Patient 2: Fibroadenoma

B mode

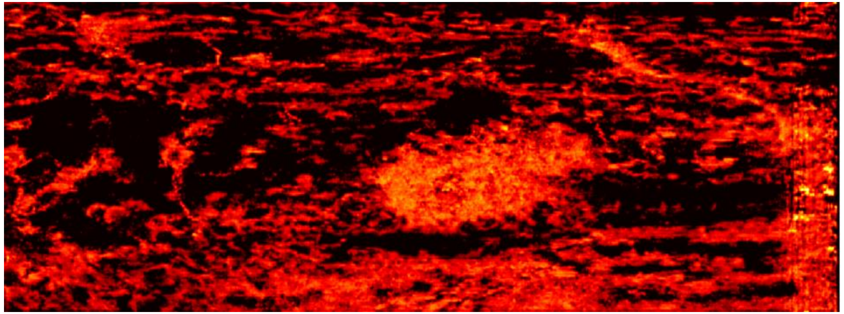


MIP



Standard maximum intensity projection. Difficult to separate lesion signal from tissue signal.

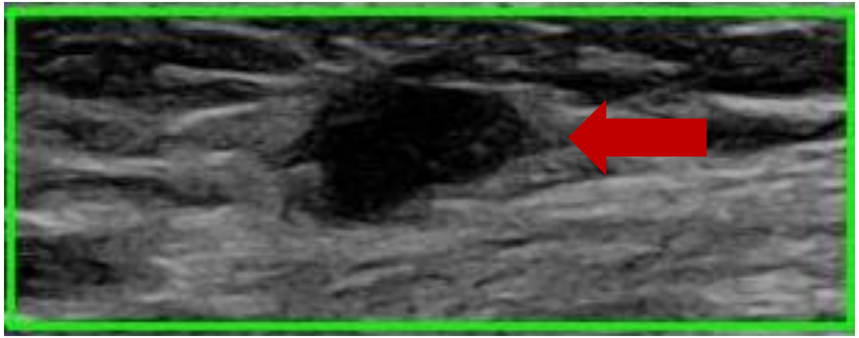
Deep unfolded ULM



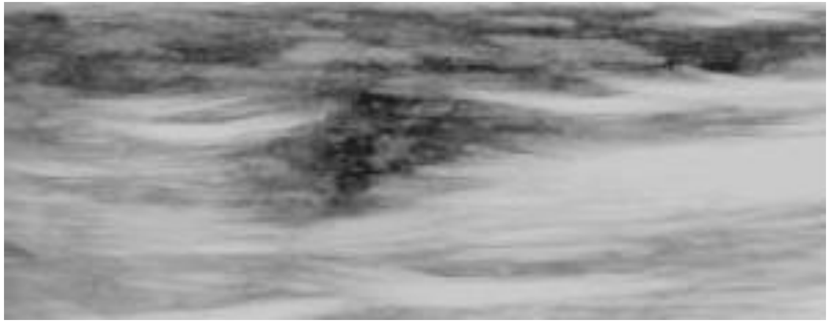
Super resolved image. Displays a highly vascularized lesion.

Patient 18: Malignant mass

B mode

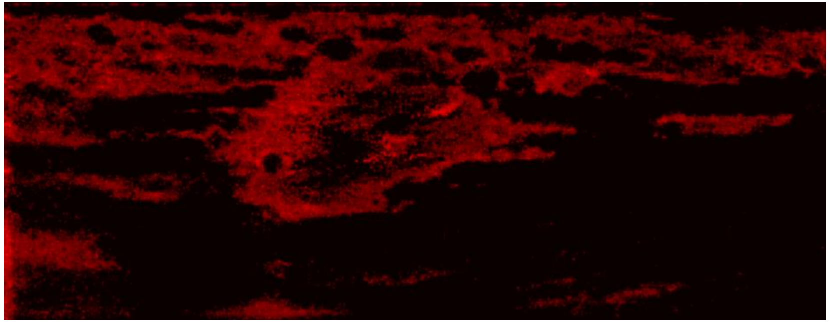


MIP

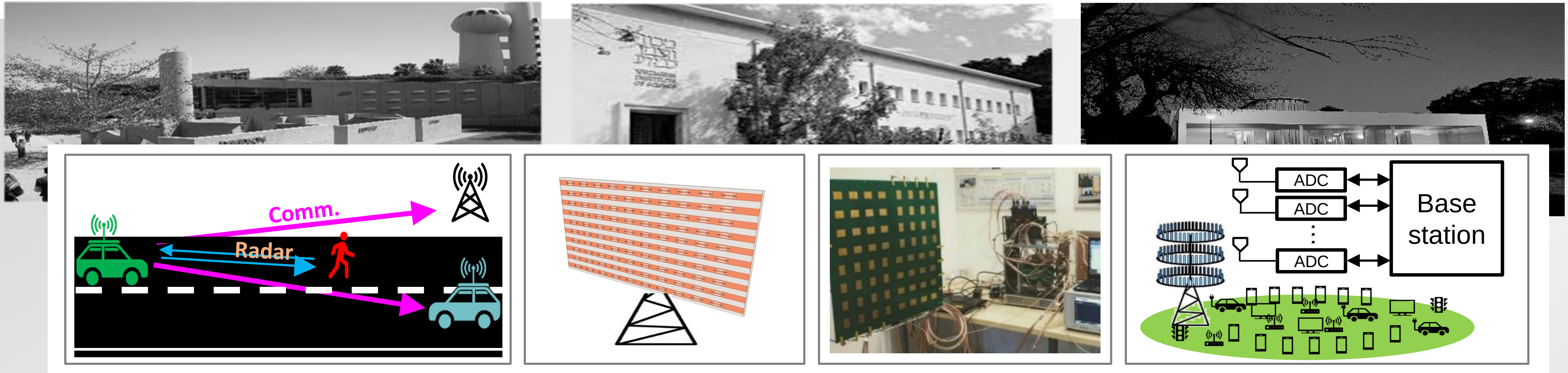


Standard maximum intensity projection. Difficult to separate lesion signal from tissue signal.

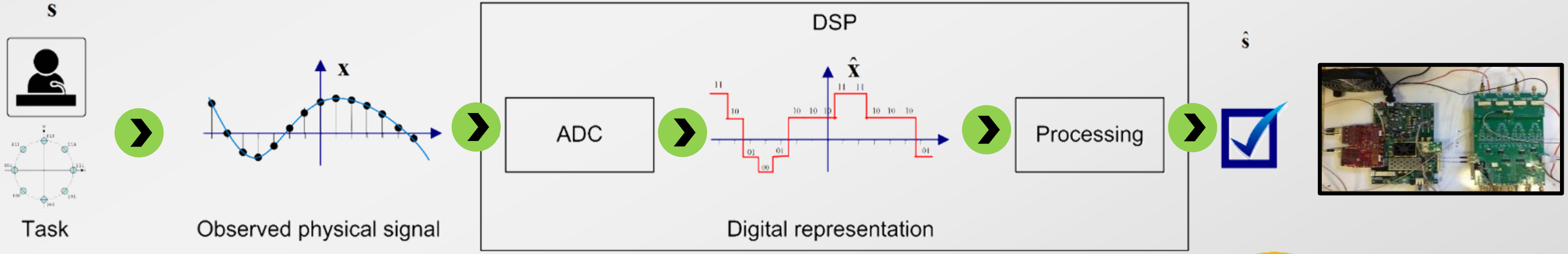
Deep unfolded ULM



Super resolved image. Displays a high vascularization at the edges of the mass and a low concentration of blood vessels at the middle.



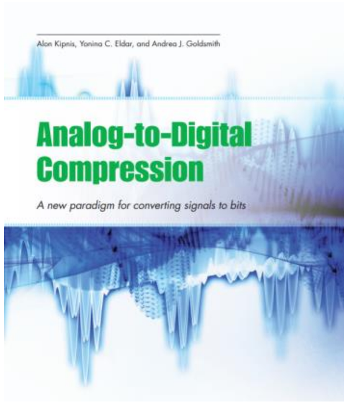
Quantization



SAMPLLAB
Signal Acquisition Modeling Processing and Learning

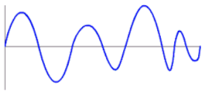
Analog to Digital Compression

> Kipnis, Goldsmith, Eldar and Weissman 17-19



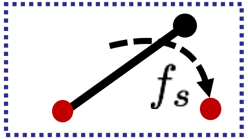
- Until now we ignored quantization
- Quantization introduces **inevitable distortion to the signal**
- Since the recovered signal will be distorted due to quantization:

Do we still need to sample at the Nyquist rate?

01001001001010010…

$x(t)$



$y[n]$ → quantizer → $\hat{y}[n]$

$f_s = \#$ samples/sec

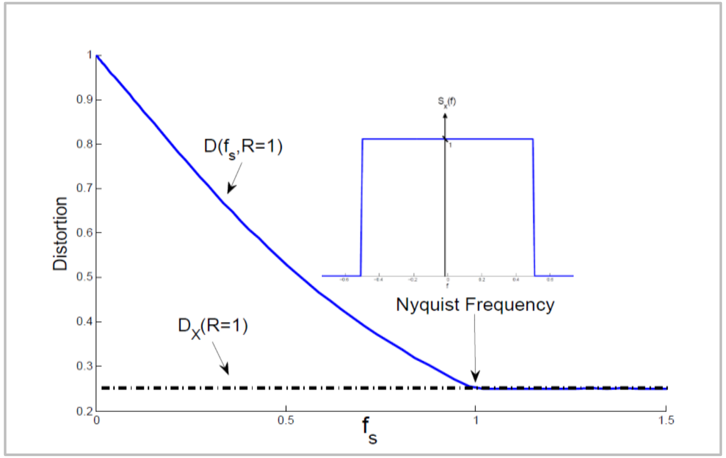
$R = f_s \log_2(\#\text{levels})$ bit/sec

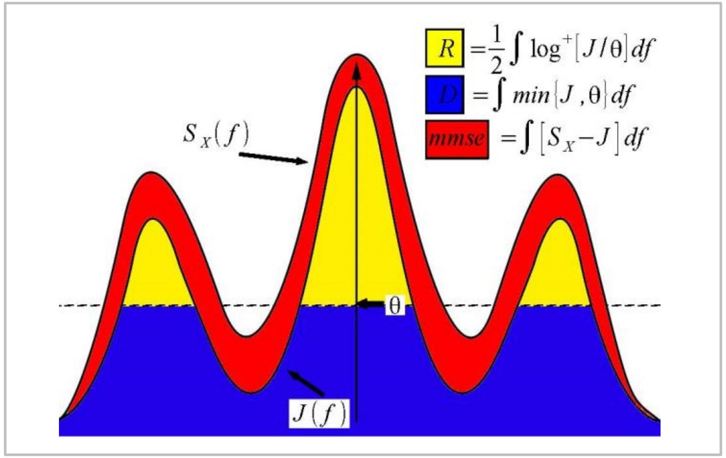
Sampling Theory

Source Coding [Shannon]

Goal: Unify sampling and rate distortion theory

Quantizing the Samples: Source Coding Perspective





- Preserve signal components above "noise floor" q, dictated by R
- Distortion corresponds to mmse error + signal components below noise floor

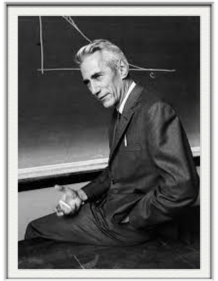
Theorem (Kipnis, Goldsmith, Eldar, Weissman 2016)

$$R(f_s,\theta) = \frac{1}{2}\int_{-\frac{fs}{2}}^{\frac{fs}{2}} \log^+\left[\tilde{S}_{X|Y}(f)/\theta\right]df$$

$$D(f_s,\theta) = mmse_{X|Y}(f_s) + \int_{-\frac{fs}{2}}^{\frac{fs}{2}} \min\{\tilde{S}_{X|Y}(f),\theta\}df$$

Optimal Sampling Rate

> Kipnis, Eldar and Goldsmith 18



Shannon [1948]

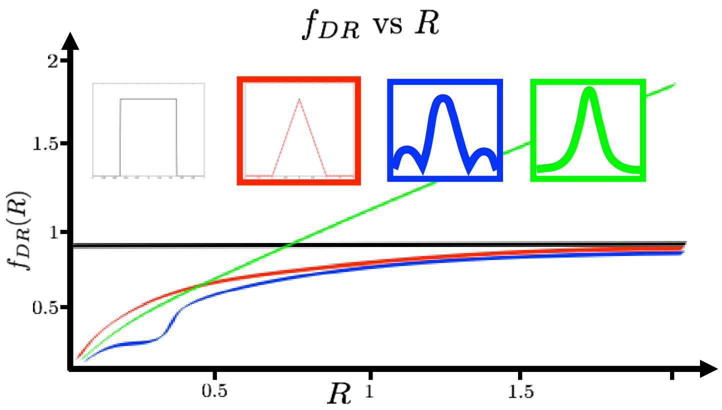
"we are not interested in exact transmission when we have a continuous source, but only in transmission to within a given tolerance"

Can we achieve D(R) by sampling below f_{Nyq}?

- Yes!
  For any non-flat PSD of the input

$$D(R, f_s) = D(R) \text{ for}$$

$$f_s \geq f_{DR}(R)!$$

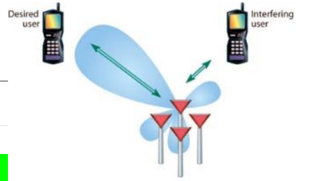


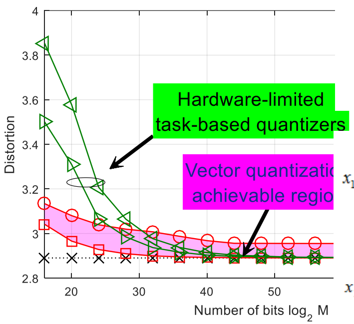
No optimality loss when sampling at sub-Nyquist (without input structure)!

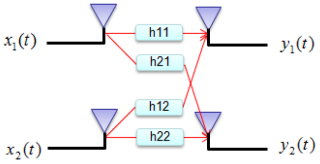
Task-Based Hardware-Limited Quantization

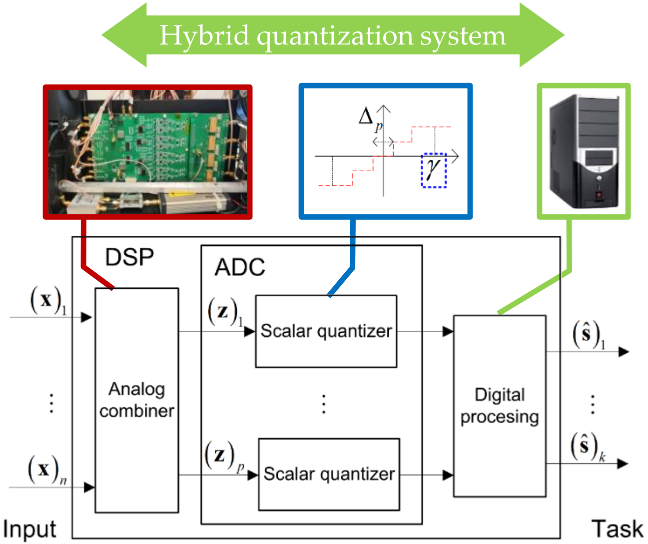
> Shlezinger, Eldar, Rodrigues 19

- Optimal quantization typically using vector quantizers
- ADCs are usually serial scalar quantizers
- Signals are often acquired for a task:
  - Channel estimation
  - Source localization…









Exploit task to reduce number of bits and simplify hardware

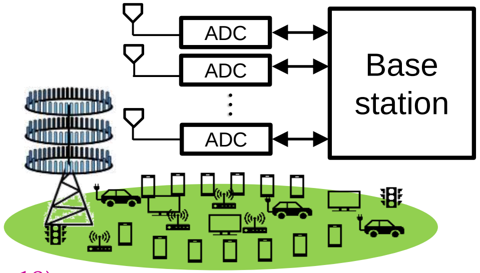
Jointly optimize in light of the task		
Analog combining	Quantizer support	Digital processing

Tools: Majorization theory, dithering, water filling

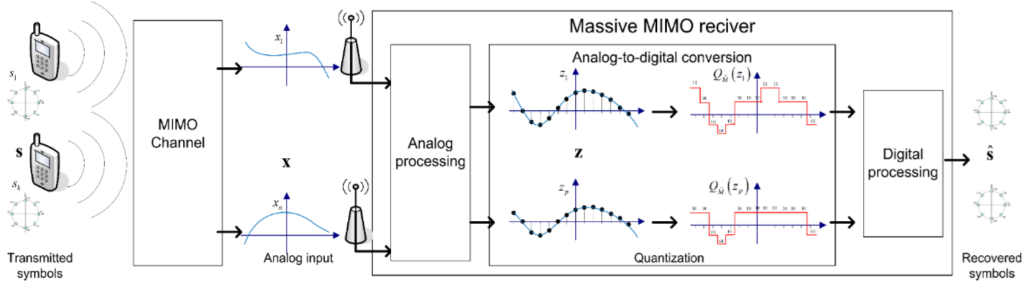
Application: Massive MIMO

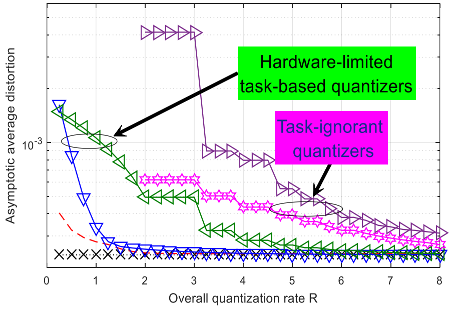
> Shlezinger, Eldar, and Rodrigues 19-20

- Next generation cellular communications
- Equip base stations with large antenna array
  - Increases throughput (Marzetta 10, Shlezinger and Eldar 19)
  - Costly in power and memory
  - Efficient quantization is essential
- Hybrid architectures are common (Mo et al 17), (Roth et al 17), (Stein and Eldar 19)….
- Lots of work on low bit ADCs: approximate ADC output and apply MMSE (Li et. al 17), (Choi, Mo, Heath 17), (Mollen et. al 17), (Mo et. al 18), (Jacobsson et. al 17), …



Jointly optimize as a task-based quantizer!

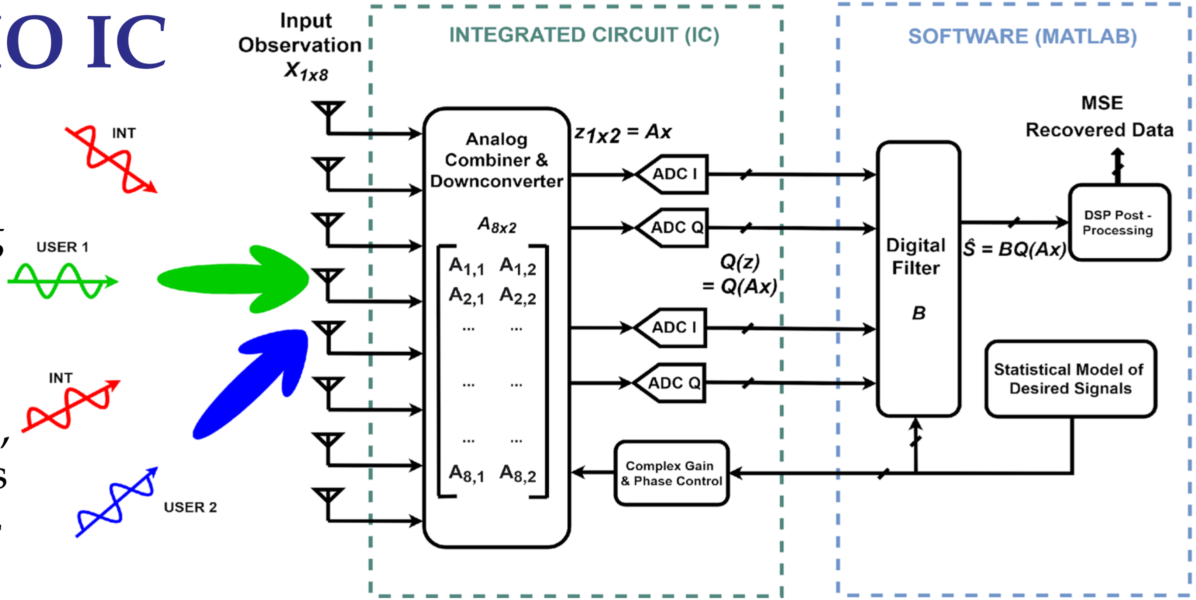


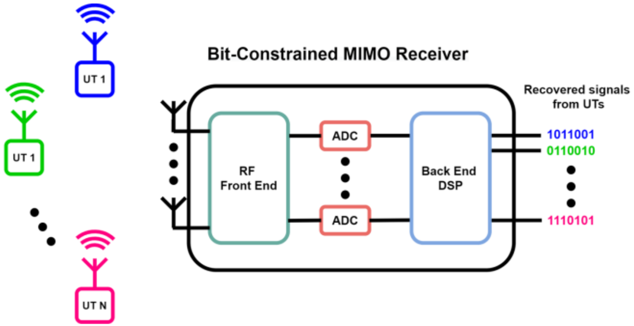


Proposed Research: Task-Based MIMO IC

> Zirtiloglu, Shlezinger, Eldar, Yazicigil `21

- Task is to minimize error vector magnitude (EVM)
- Task-oriented architecture using low quantization rate
- Configuring optimal analog pre-quantization matrix A and digital post-quantization filter B, using statistical model of signals
- Analog/digital beamforming for spatial interferer rejection



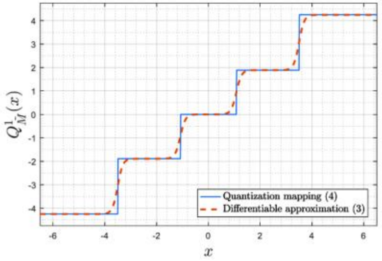


	Fully Digital (Conventional)	Orthogonal Beamforming (Golabighezelahmad et al 19)	Proposed Task-Based MIMO
RF Front End Power	LOW	HIGH	LOW
ADC Power	HIGH	LOW	LOW
Low Quantization Rate	✗	✗	✓
Spatial Filtering	✗	✓	✓

Deep Task-Based Quantization

> Shlezinger and Eldar 19

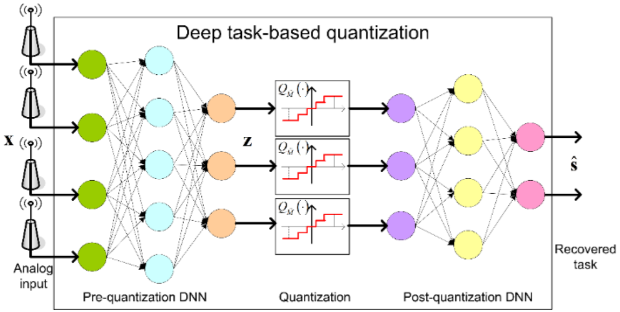
› Data-driven task-based quantization

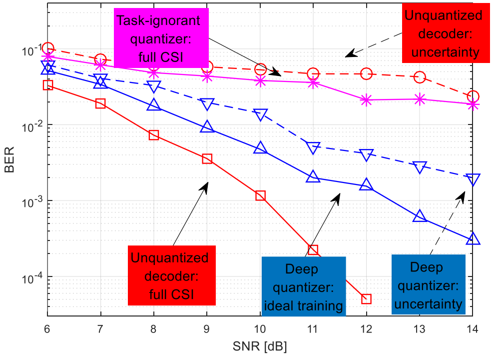


› Learn mapping from training
› Model-ignorant

Structure in the quantizer + the task

Simple and robust deep quantizers that achieve optimal performance!



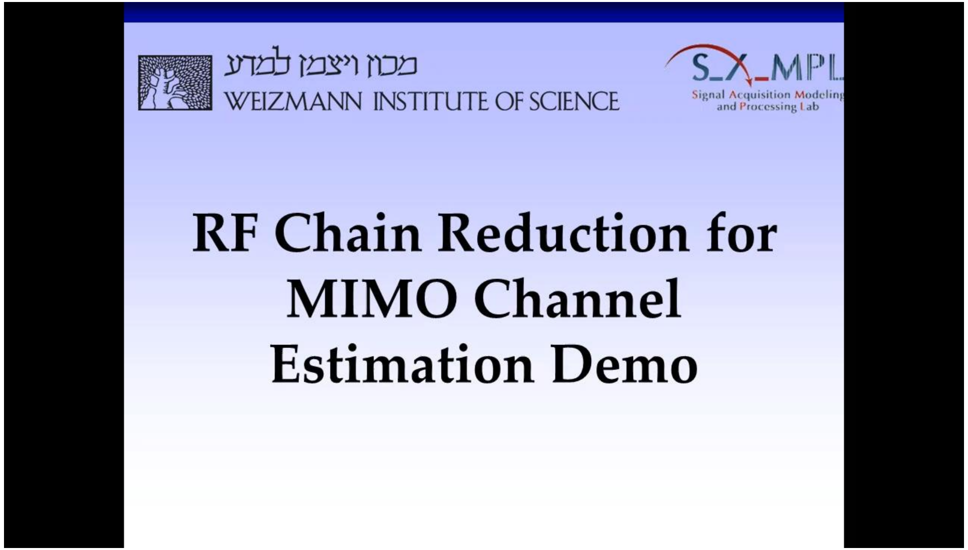


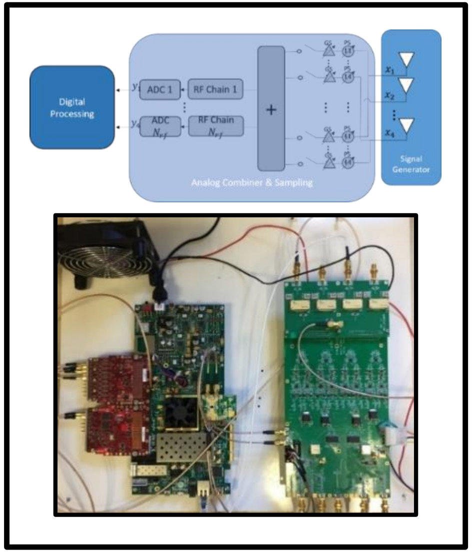
Massive MIMO Demo

> Ioushua et. al 18-20

Practical MIMO receiver with fewer RF chains than antennas + low bit samplers

- Significantly reduce power and hardware cost
- Similar performance!

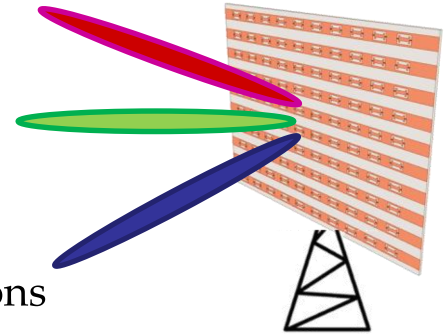


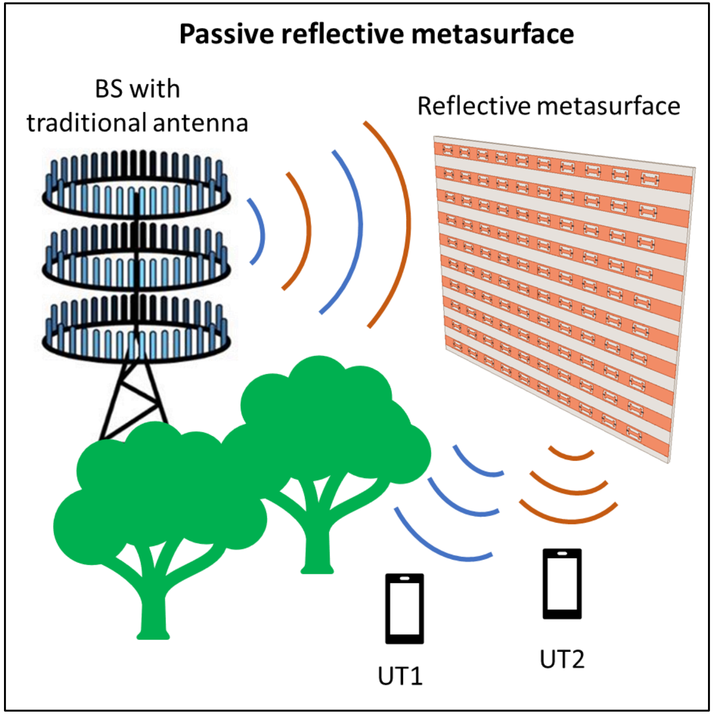


Task-based quantizers lead to simple low power hardware for comm and radar systems without degrading performance!

Dynamic Metasurface Antennas

- Emerging antenna technology:
  - Scalable
  - Low power
- Dynamically configurable radiation pattern
- Applications:
  - Microwave imaging
  - Radar systems
  - Satellite communications
- Intelligent reflective surfaces **(Huang et al, TWC 19)**



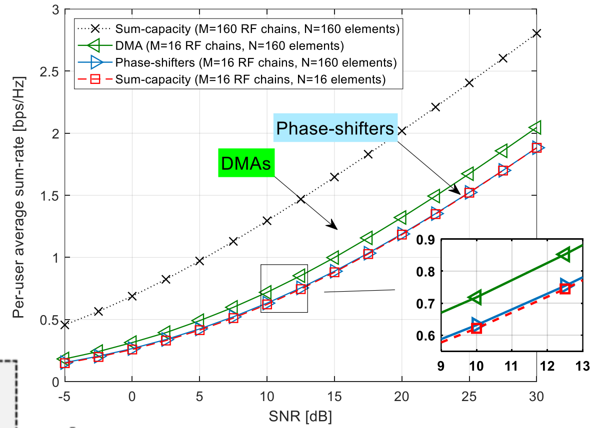


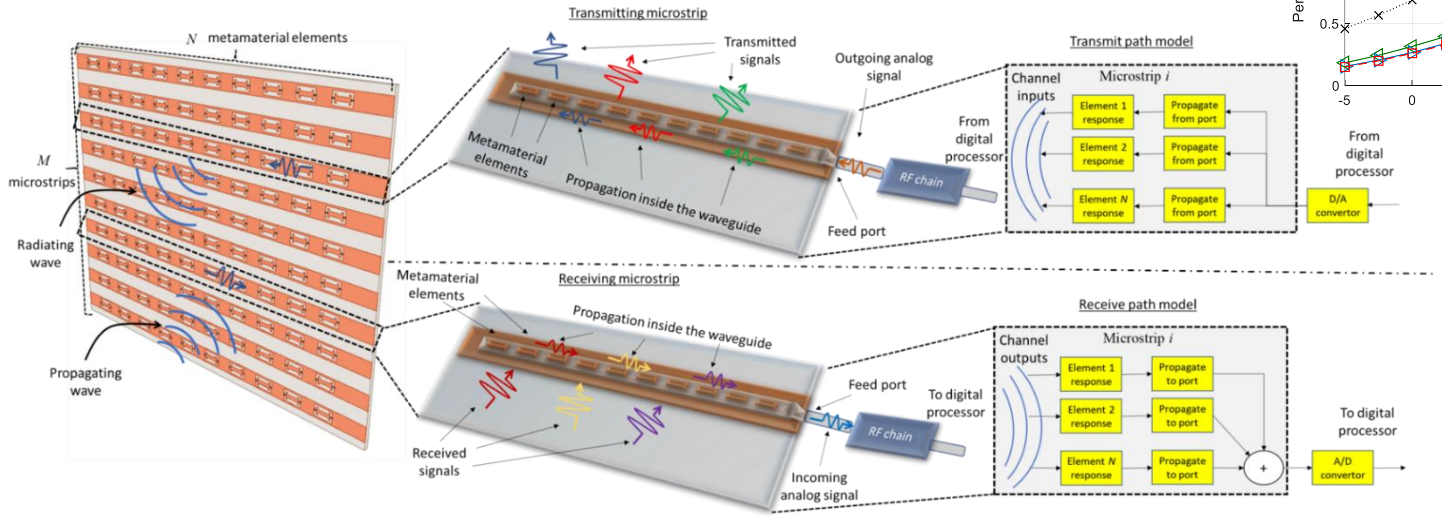
Metasurfaces for Analog Precoding

> Shlezinger et. al 19-21
> Collaboration with the group of Prof. David Smith

Alternative approach to dedicated analog precoder hardware

- Inherent tunable analog precoding in the antenna structure
- Low power, small hardware
- Enhanced frequency-selective analog processing

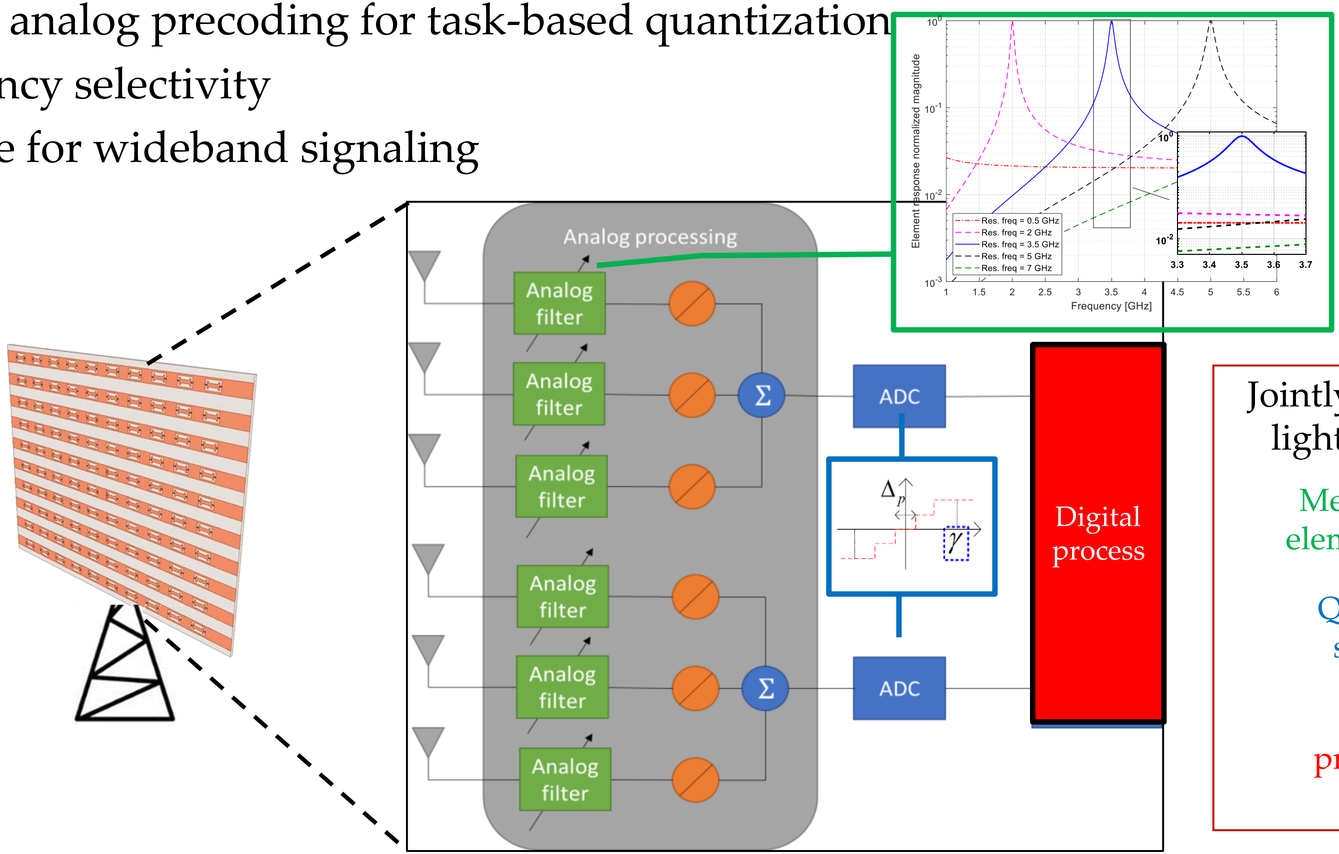




Metasurface Antennas with Low-Bit ADCs

> Wang et al. 20

- Exploit analog precoding for task-based quantization
- Frequency selectivity
- Suitable for wideband signaling



Jointly optimize in light of the task

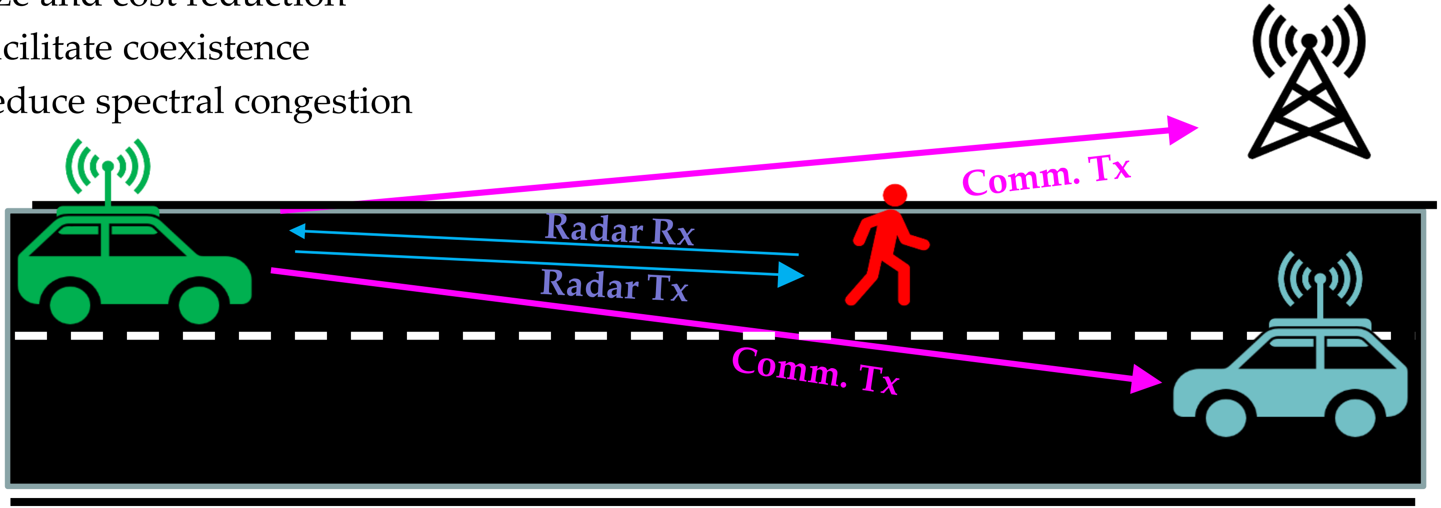
Metamaterial element setting

Quantizer support

Digital processing

Joint Radar-Communications for Autonomous Driving

- We have seen ways to reduce size, power, space in both radar and comm
- Can we combine?
- Autonomous cars constantly assess their environment requiring wireless communication transceivers and radars
- Motivates designing these functionalities jointly
- Dual-function radar communication (DFRC) systems:
  - Size and cost reduction
  - Facilitate coexistence
  - Reduce spectral congestion

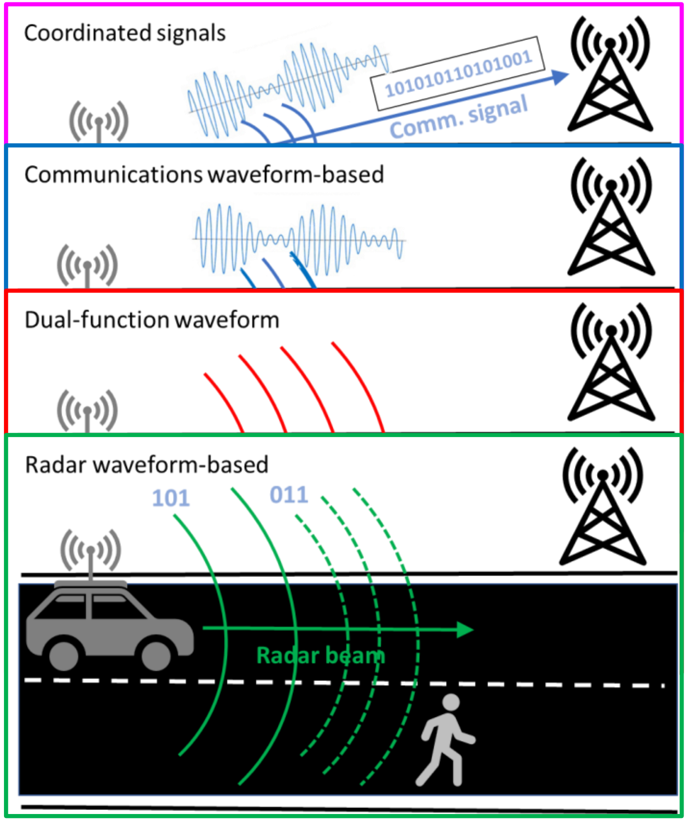


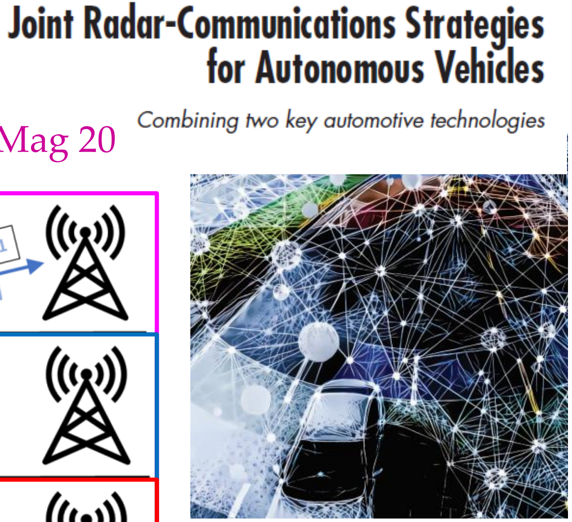
DFRC Strategies

Leading design approaches:

- Separate coordinated signals
  - Beamform / orthogonalization
- Communication waveform
  - OFDM radar
- Dual-function waveform
  - Dedicated design
- Radar waveform
  - Embed message

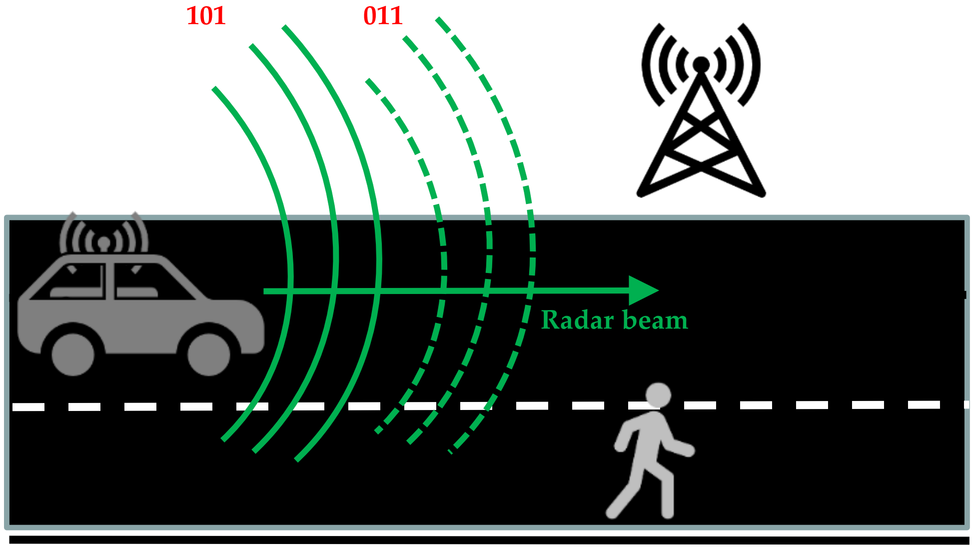
> Ma et al. SPMag 20





Embedding Information in Radar Waveforms

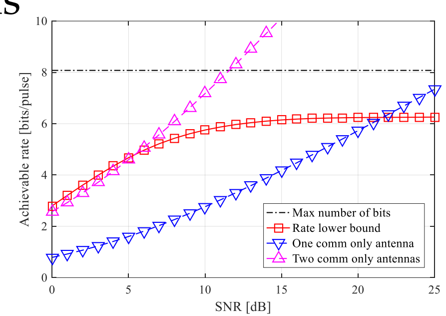
- Convey digital messages with radar signals:
  - Embed bits in the waveform parameters
  - Index modulation: Frequencies, antenna elements
- Benefits
  - Use conventional radar signals
  - Minimal radar degradation
- Drawbacks
  - Limited bit rates
  - Challenging decoding

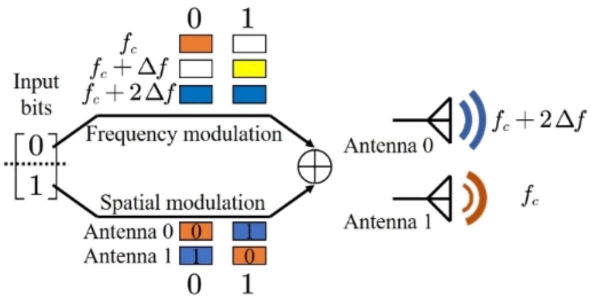


MAJoRCom: Multi-carrier Agile Joint Radar Communications

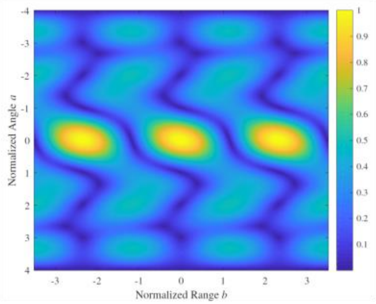
> Huang et al. 20

› Use only radar waveforms
› Embed information in:
  › Frequency selection
  › Antenna allocation
› Spectrally efficient:
  • Upper bound
  • Lower bound
  • One dedicated antenna
  • Two dedicated antennas
› Angular resolution:

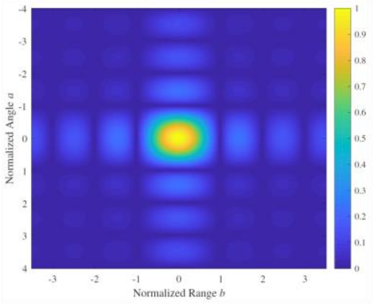




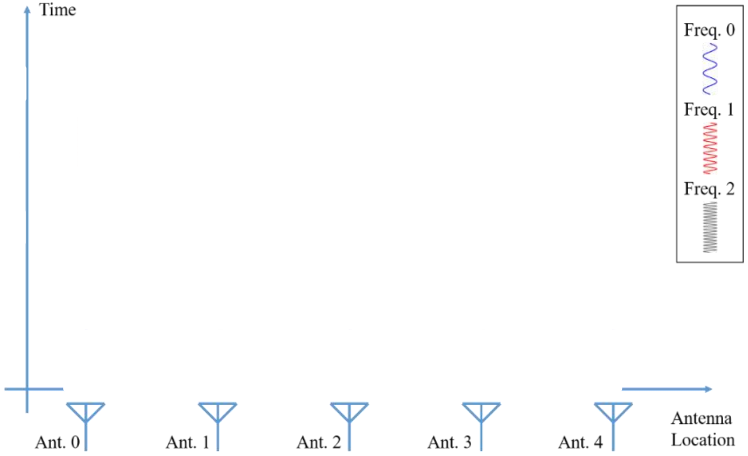
Comparable to using dedicated comm. antennas *without affecting radar*



Instantaneous



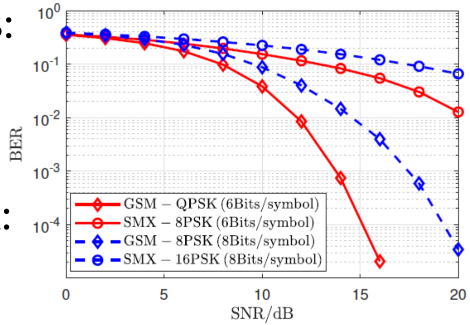
Expected

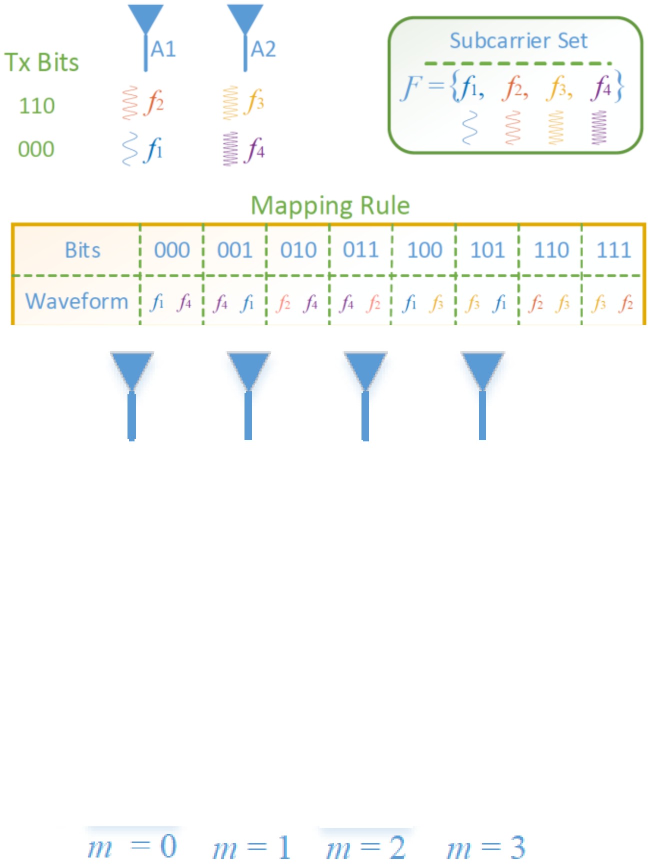


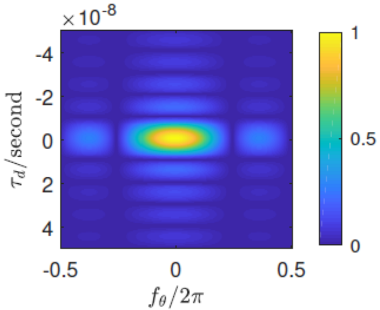
SpaCoR: Spatial Modulation Based Communication-Radar

> Ma et al. 20

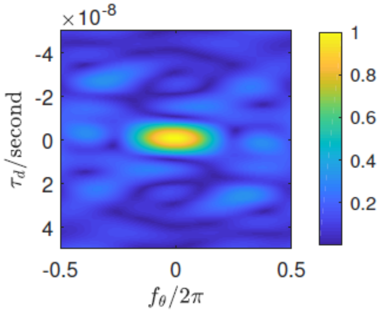
- Orthogonal transmissions:
  - Distinct bands
  - Distinct antennas
- Toggle antenna allocation:
  - Spatial modulation
  - Spatial agility
  - Improved resolution and throughput







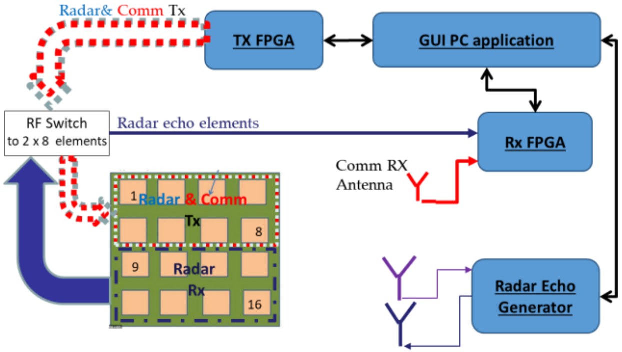
(a) Full Antenna Array

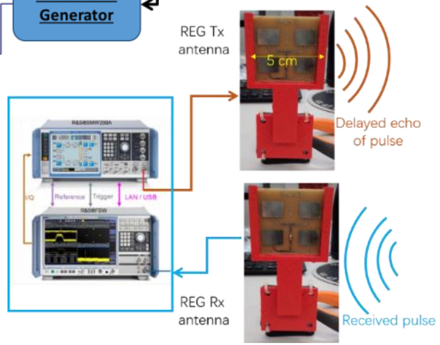


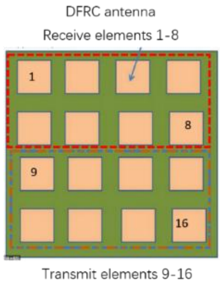
(b) SpaCoR

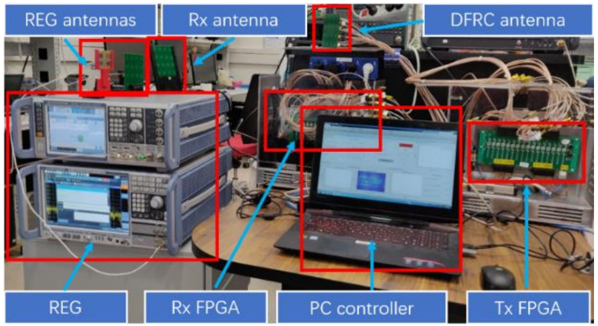
Hardware Prototype

- Using over-the-air signaling
- 16 antenna elements
- Radar echo generator (REG)





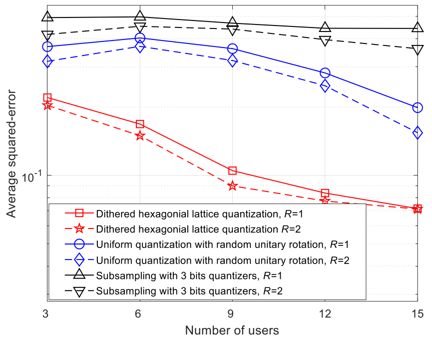


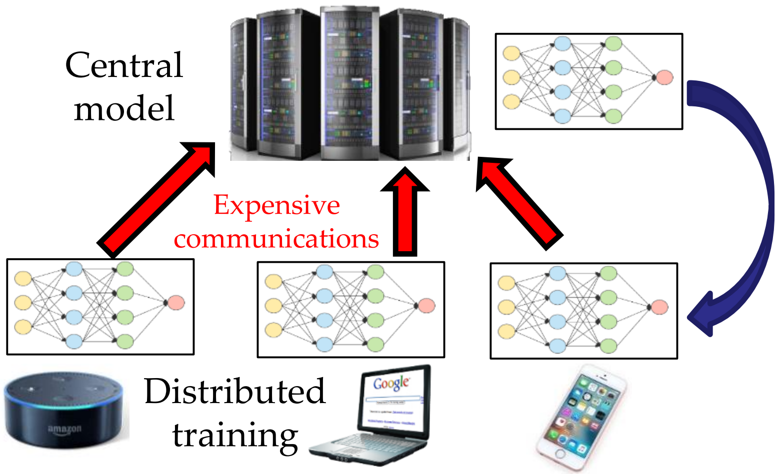


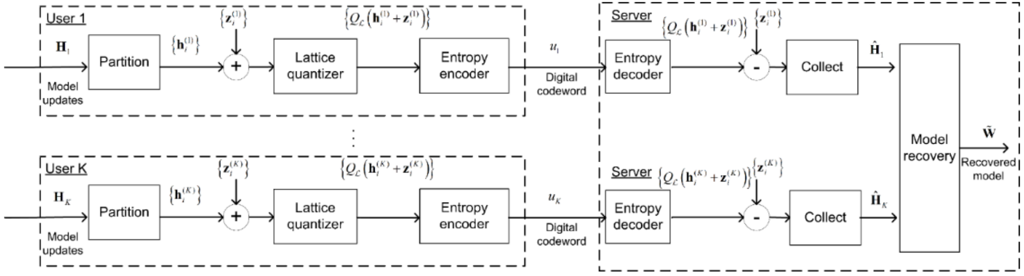
Task-Based Quantization for Federated Learning

> Shlezinger, Chen, Eldar, Poor, Cui, 19

- Train on edge devices
- Quantize model updates
- Aggregate quantized weights





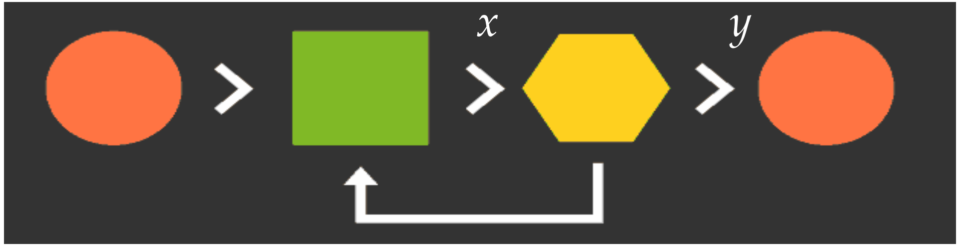


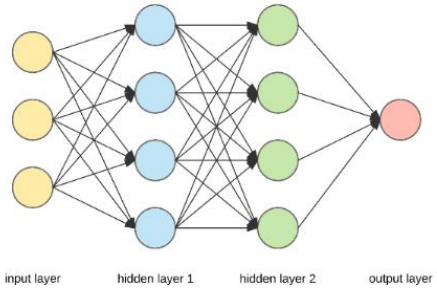
Reliable centralized model with less communication



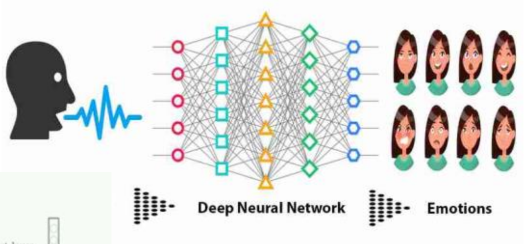
Part 3:

Model-based deep learning

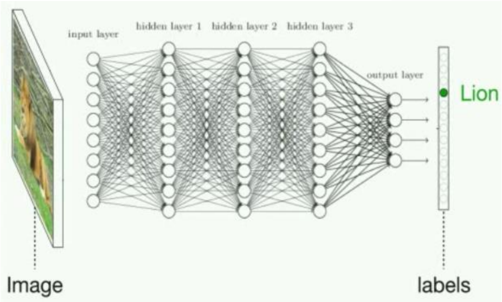




Black-Box Deep Learning



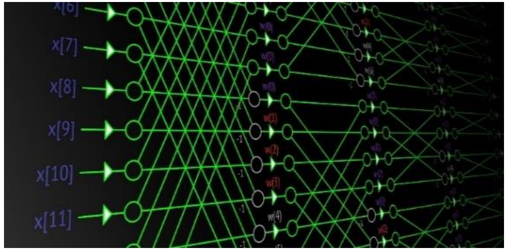
- Deep neural networks (DNNs) achieve superior performance in:
  - Computer vision
  - Speech processing
  - Problems which are hard to tackle with models

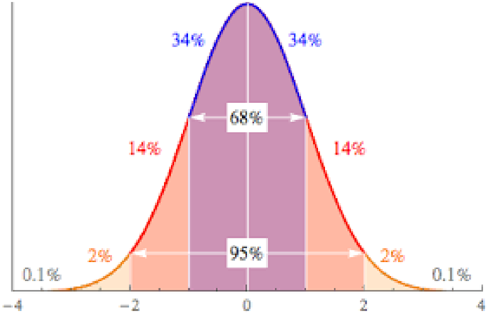


- Challenges:
  - Large training sets
  - Interpretability?
  - Robustness?
  - Generalization limited
  - Generic architectures

Model Based Signal Processing

- Signal processing is based on modeling
- Can incorporate domain knowledge and structure
- Allows inference from relatively small amounts of data
- Analytical techniques to assess quality of the output





However:

- Requires accurate model knowledge
- Inference can be slow

Combining model-based algorithms and deep learning:
Compact, interpretable, and simple to train data-driven systems!

Model-Based vs. Deep Learning

- Model-based signal processing:

Input y

(Measurement)

Optimize a metric function

$f(g(x), y)$

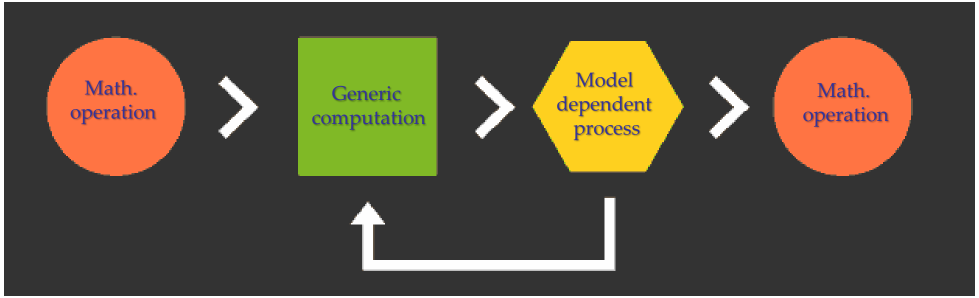
Output x

Model-Based vs. Deep Learning

- Model-based signal processing:

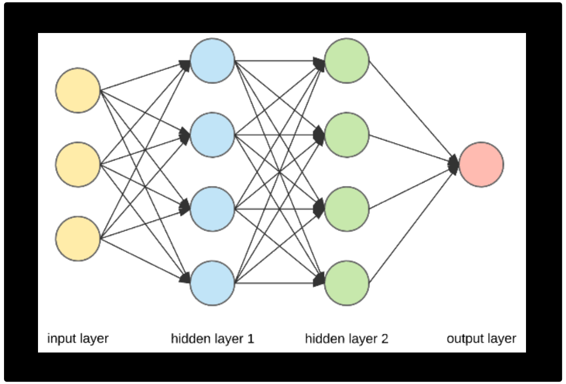
Input y

(Measurement)



Output x

- Deep learning:



Many
Inputs

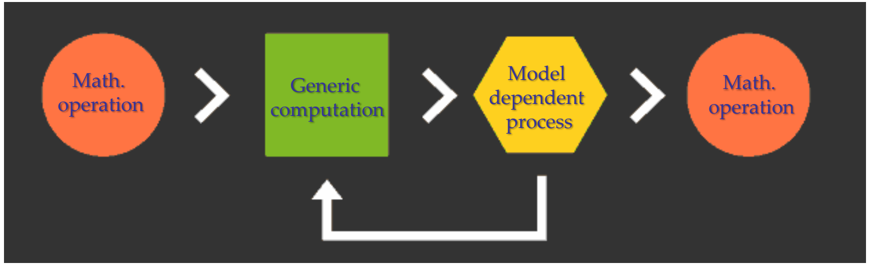
New y

Many
Outputs

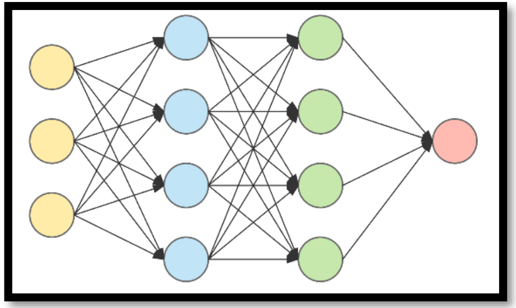
x

Model-Based Deep Learning

› Model-based signal processing:



› Deep learning:



› How to combine?

1. Integrate model-based algorithms into deep networks

Deep unfolding / unrolling

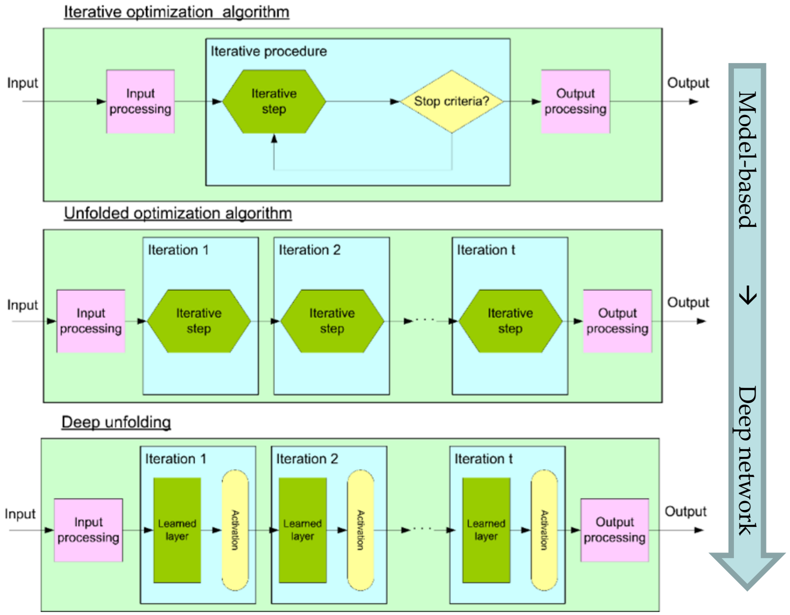
2. Integrate deep networks into model-based algorithms

Data-driven hybrid algorithms

Deep Unfolding

> Gregor and LeCun 10; Hershey, Le Roux, and Weininger 14

- Deep networks inspired by iterative model-based algorithm:
  - Unfold iterations into layers
  - Learn parameters of the layer from data
  - Model-driven network
- Benefits:
  - Faster convergence
  - Less trainable parameters
  - Interpretable network
  - Better performance from less training data



Vishal Monga, Yuelong Li, and Yonina C. Eldar

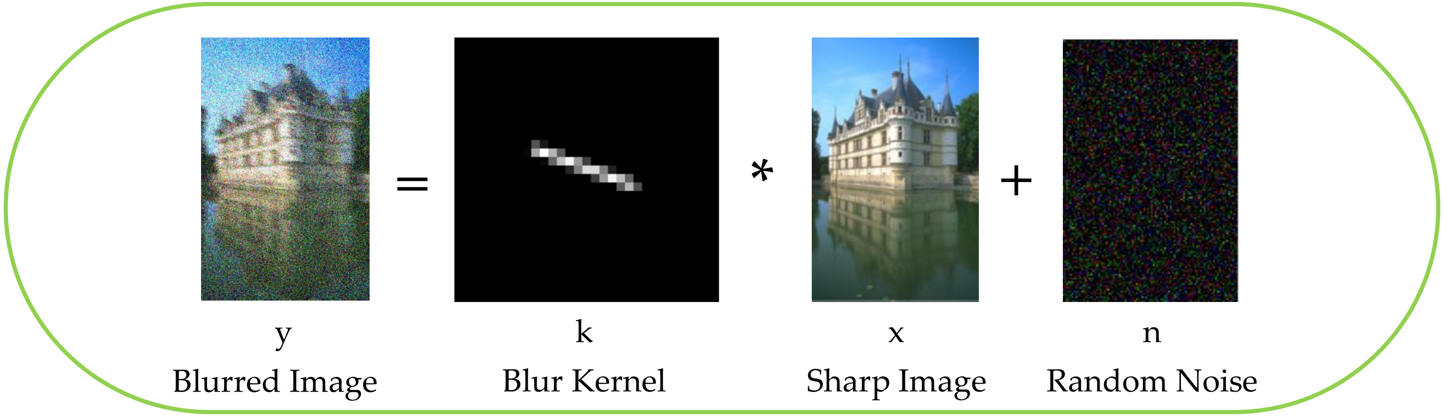
Recent review in SP Magazine

Algorithm Unrolling

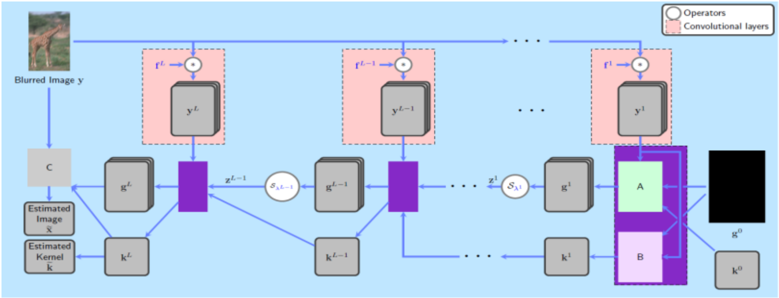
Interpretable, efficient deep learning for signal and image processing

DUBLID: Deep Unrolling for Blind Deblurring

> Li, Tofighi, Monga and Eldar, 19



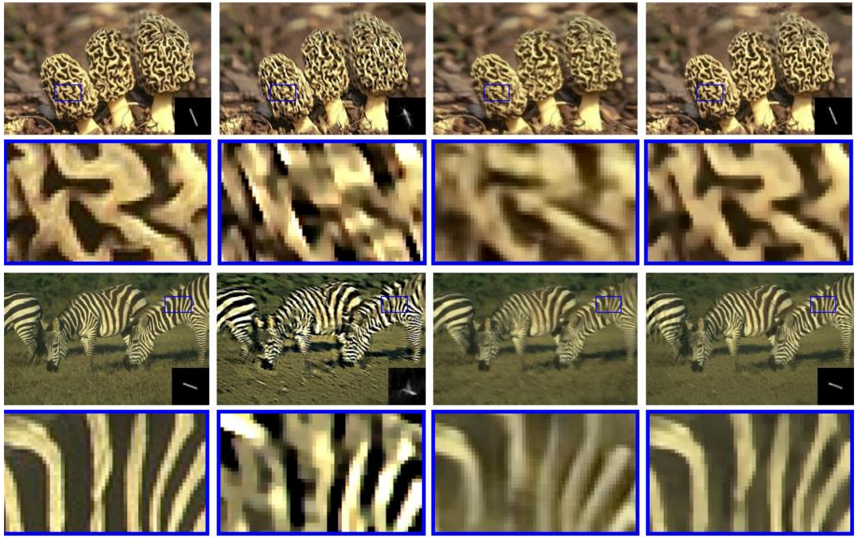
- Many deblurring methods based on optimization (e.g. total variation)
- We perform total variation in the gradient domain $\nabla \mathbf{y} \approx \mathbf{k} * \nabla \mathbf{x}$
- We solve the problem by a variable splitting approach and then unfold



Deblurring Results

> Li, Tofighi, Monga and Eldar, 19

- Training based on BSDS500 dataset
- Blur kernels of linear motion with different lengths and angles



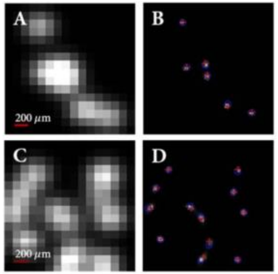
(a) truth (b) Perrone *et. al* (c) Nah *et. al* (d) DUBLID

Superior performance, parameter free and computational benefits. All code available online.

Super-resolution via Deep Learning

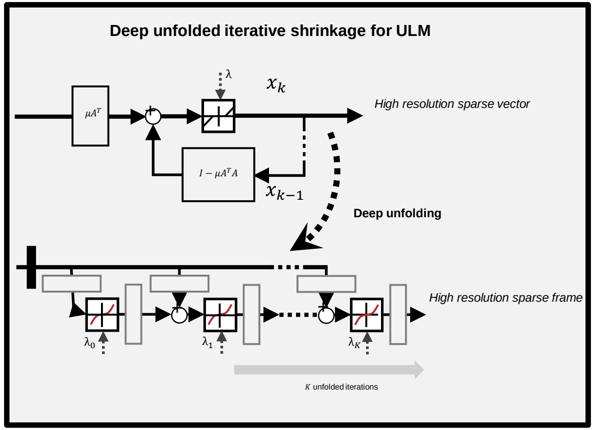
> Van Sloun et. al. 2018

- Resolve overlapping bubbles via deep network scheme
  - Improved performance over sparse recovery methods
  - Faster execution time
- Relies on a learned ISTA approach via unrolling

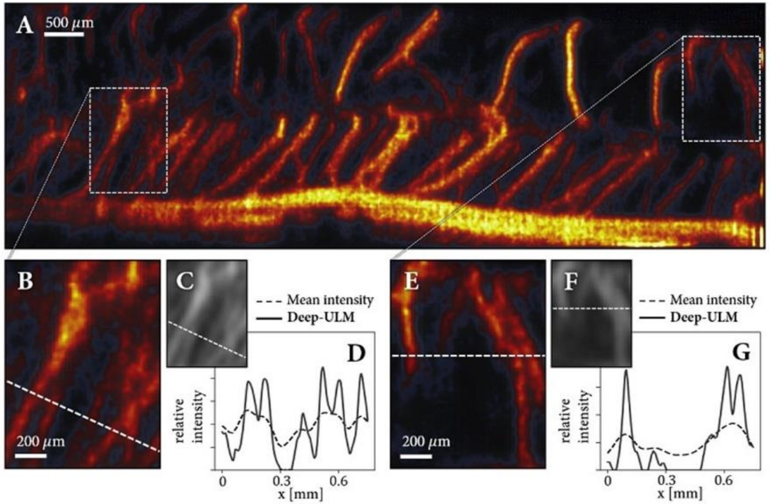


- **Cost function:**

$$||f(x|\theta) - G * y||_2^2 + \lambda||f(x|\theta)||_1$$



Super-resolution of rat spinal cord vasculature

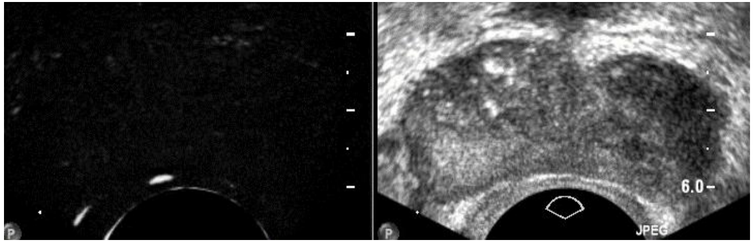


Removing Tissue Background via Deep Learning

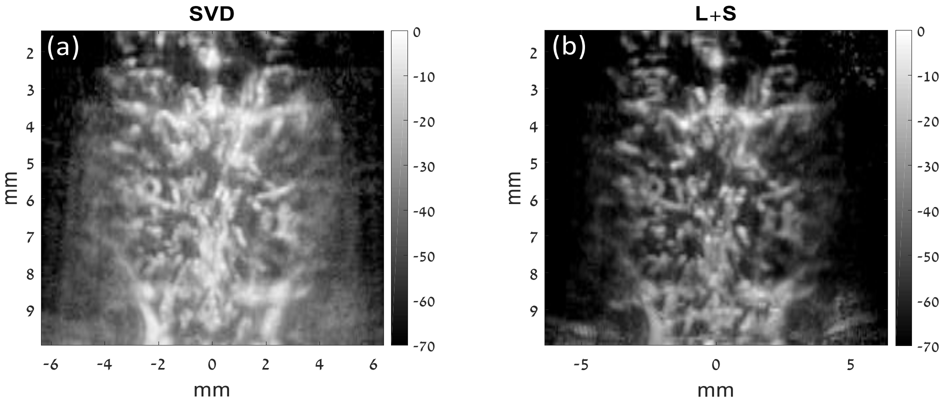
CORONA: Convolutional rObust pRincipal cOmpoNent Analysis

> Solomon et. al. 2018

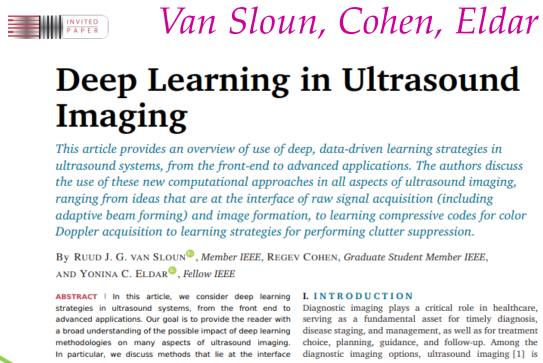
- Blood signal is cluttered by unwanted tissue
- We use the model:
  - low rank (background) +
  - sparse (contrast signal)
- Use model based deep learning
- Improved performance in terms of noise, frame rate



In-vivo contrast rat brain scan



Van Sloun, Cohen, Eldar



INVITED PAPER

Deep Learning in Ultrasound Imaging

This article provides an overview of use of deep, data-driven learning strategies in ultrasound systems, from the front-end to advanced applications. The authors discuss the use of these new computational approaches in all aspects of ultrasound imaging, ranging from ideas that are at the interface of raw signal acquisition (including adaptive beam forming) and image formation, to learning compressive codes for color Doppler acquisition to learning strategies for performing clutter suppression.

By Ruud J. G. van Sloun, *Member IEEE*, Regev Cohen, *Graduate Student Member IEEE*, and Yonina C. Eldar, *Fellow IEEE*

ABSTRACT | In this article, we consider deep learning strategies in ultrasound systems, from the front end to advanced applications. Our goal is to provide the reader with a broad understanding of the possible impact of deep learning methodologies on many aspects of ultrasound imaging. In particular, we discuss methods that lie at the interface

I. INTRODUCTION
Diagnostic imaging plays a critical role in healthcare, serving as a fundamental asset for timely diagnosis, disease staging, and management, as well as for treatment choice, planning, guidance, and follow-up. Among the diagnostic imaging options, ultrasound imaging [1] is

DL for Clutter Suppression

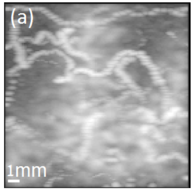
Low-rank + sparse model (L+S, RPCA)

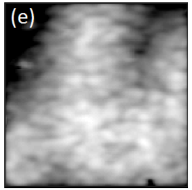
$$\min_{\mathbf{L},\mathbf{S}} \frac{1}{2}||\mathbf{D}-\mathbf{L}-\mathbf{S}||_F^2 + \lambda_1||\mathbf{L}||_* + \lambda_2||\mathbf{S}||_{1,2}$$

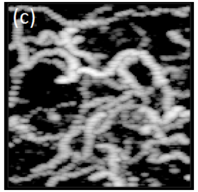
Data

Low-rank tissue clutter

Sparse MBs





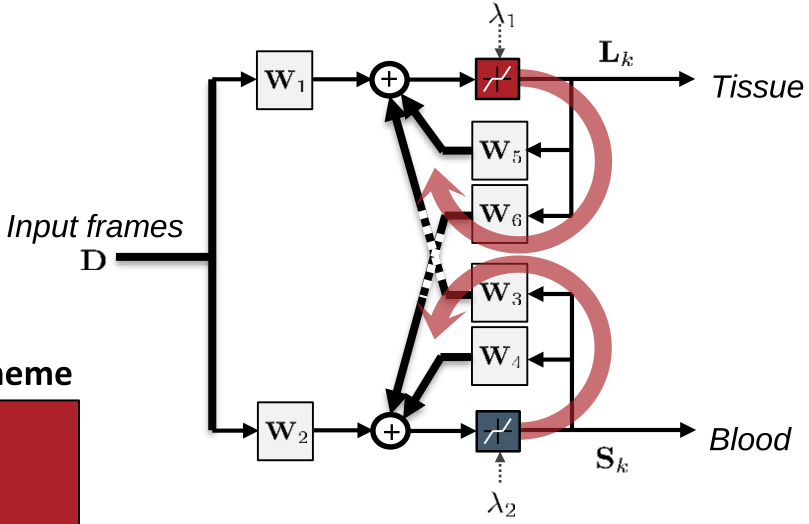


Iterative proximal gradient scheme

$$\mathbf{L}^{k+1} = \mathcal{SVT}_{\lambda_1/2}\left(\frac{1}{2}\mathbf{L}^k - \mathbf{S}^k + \mathbf{D}\right)$$

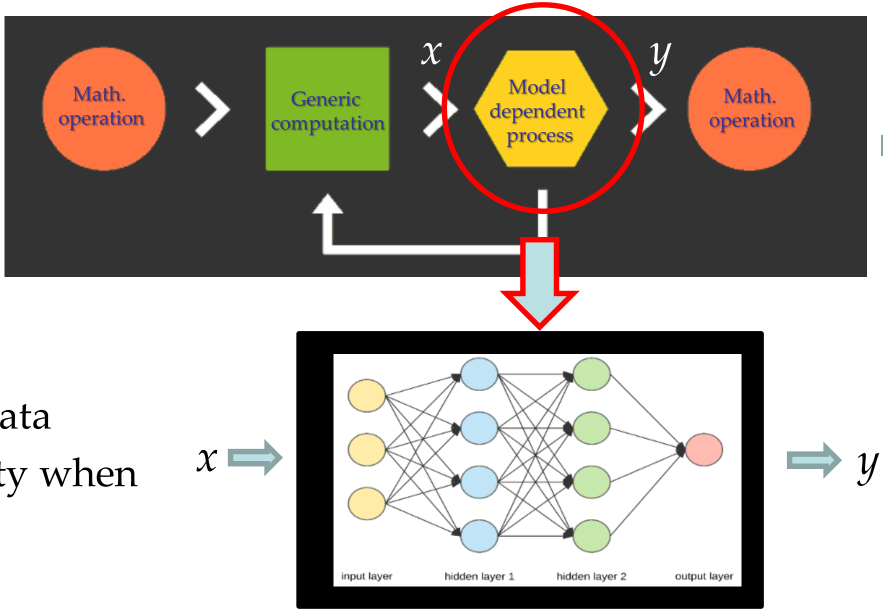
$$\mathbf{S}^{k+1} = \mathcal{T}_{\lambda_2/2}\left(\frac{1}{2}\mathbf{S}^k - \mathbf{L}^k + \mathbf{D}\right)$$

ISTA for RPCA



Data Driven Hybrid Algorithms

Input



Output

x

y

Advantages:

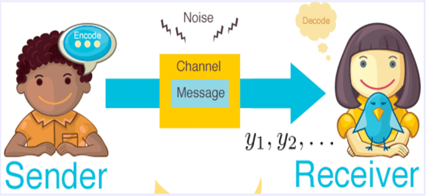
- Limited training data
- Maintain optimality when no uncertainty
- Allows for model distortions
- Once trained, easy computation

Recent review: Nariman et. al,"Data-Driven Symbol Detection via Model-Based Machine Learning"

Viterbinet: Symbol Detection with Unknown Channels

> Shlezinger, Farsad, Eldar and Goldsmith 19

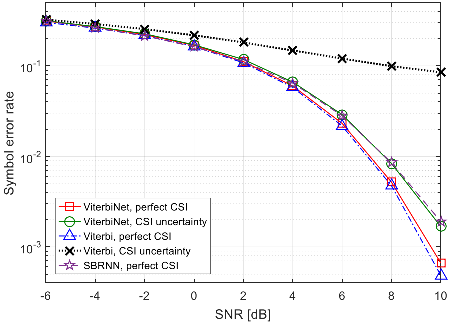
$s_1, s_2, \ldots$

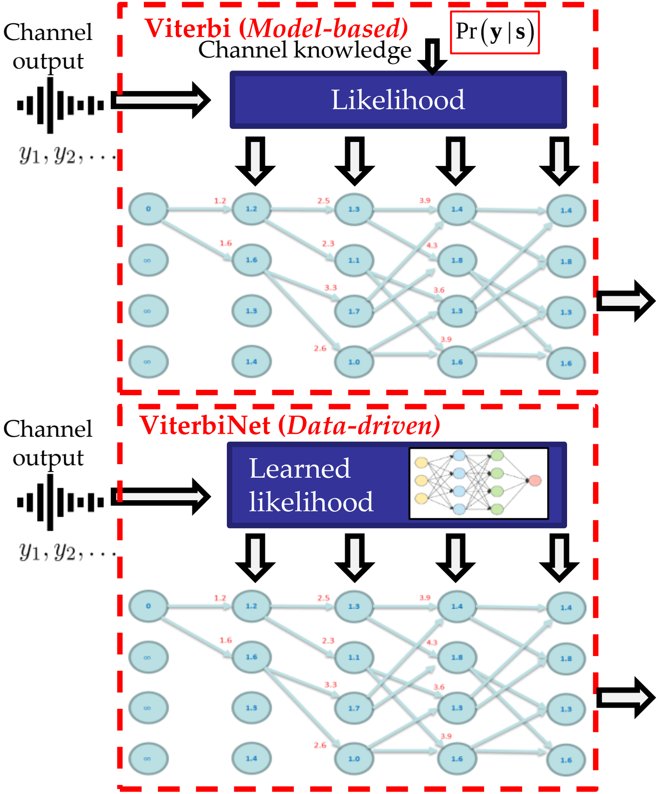


$\hat{s}_1, \hat{s}_2, \ldots$

- Viterbi detection algorithm
- Requires channel knowledge
- Viterbinet: Model based deep detection
- Unknown computations → DNNs

Optimal symbol detection from minimal training

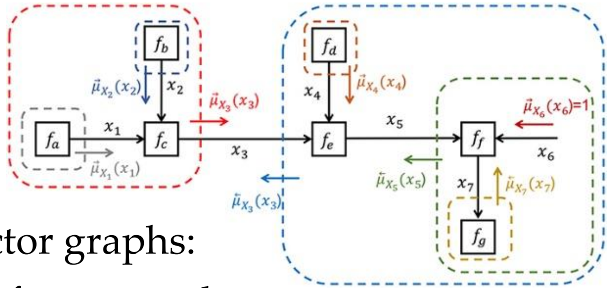




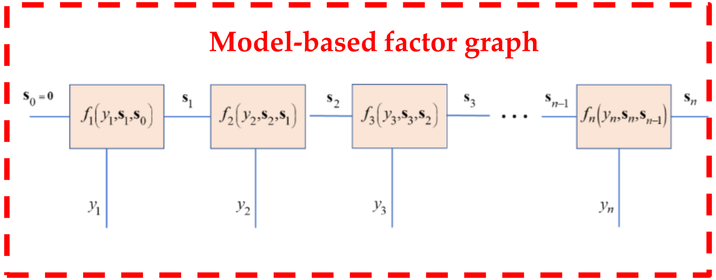
Data-Driven Factor Graph Methods

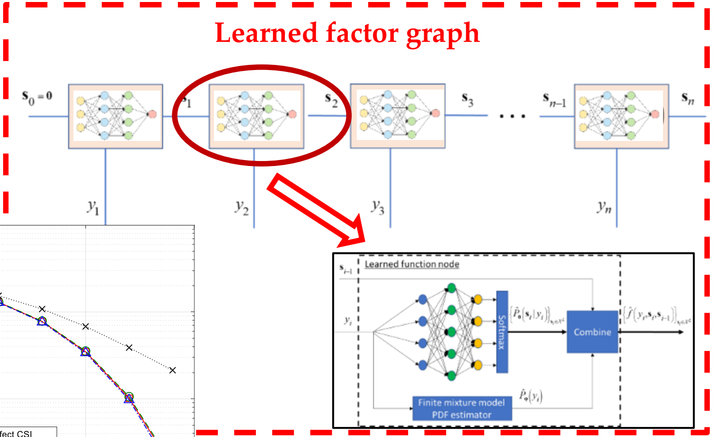
> Shlezinger, Farsad, Eldar and Goldsmith 20

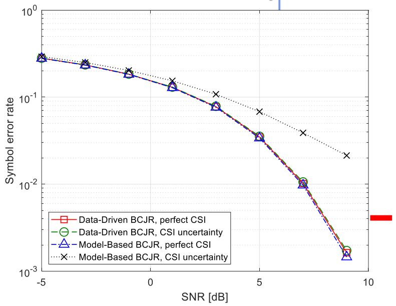
- A family of signal processing algorithms
  - Represent distribution as graph
  - Message passing



- Data-driven factor graphs:
  - Learn the factor graph
  - Message passing over graph
- Example: BCJRnet
  - Learned BCJR detector:





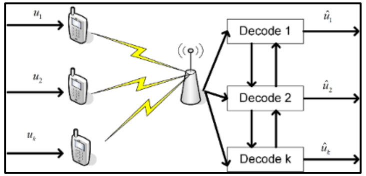


Learned MAP symbol detection

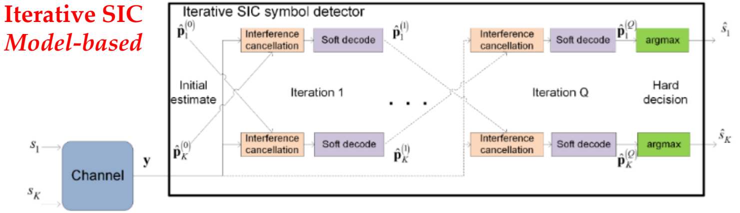
DeepSIC: Deep Soft Interference Cancellation for Massive MIMO

> Shlezinger, Fu and Eldar 19

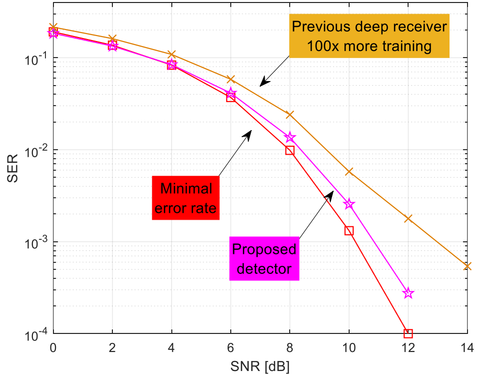
- Massive MIMO symbol detection



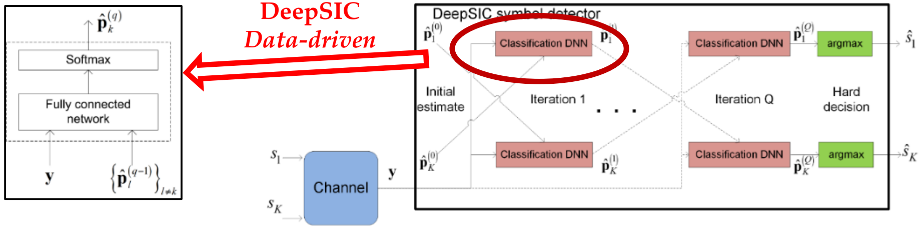
Iterative SIC
Model-based

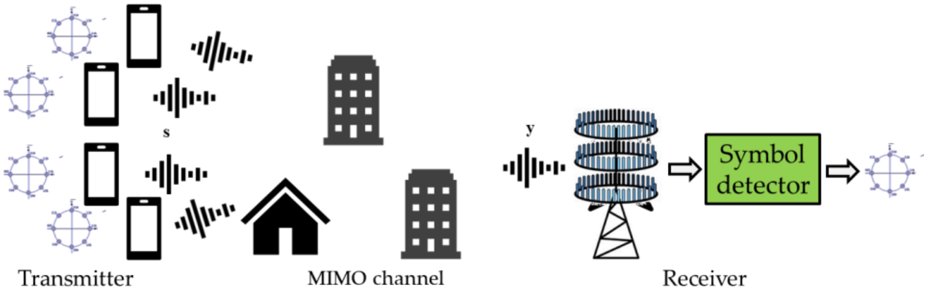


- Learn how to cancel interference



DeepSIC
Data-driven





No channel knowledge
Applicable in non-linear channels

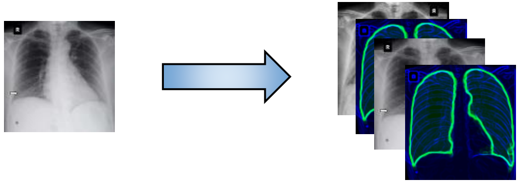
COVID19 Task Force

- Put together a task force of 4 hospitals and AI experts
- COVID19 detection using Xray: Over 90% detection rate! (PCR achieves 70%)
- Based on model-based features
- Starting to deploy in Beilinson
- Next steps in project including postcovid

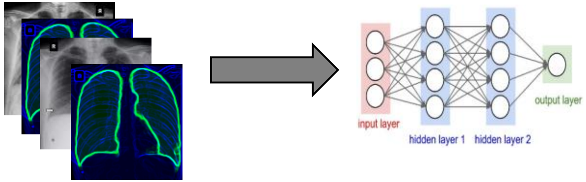
COVID-19 Classification of X-ray Images Using Deep Neural Networks

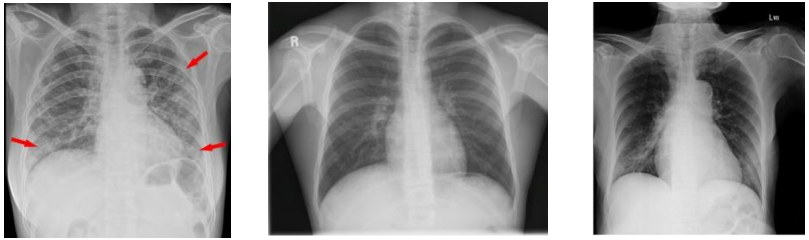
Elisha Goldstein[1]*, Daphna Keidar[2]*, Daniel Yaron[3]*, Yair Shachar[4], Ayelet Blass, Leonid Charbinsky MD[5], Israel Aharony MD[5], Liza Lifshitz MD[5], Dimitri Lumelsky MD[5], Ziv Neeman MD[5], Matti Mizrachi MD [6], Majd Hajouj MD [6], Nethanel Eizenbach MD[6], Eyal Sela MD[6], Chedva S Weiss MD [7], Philip Levin MD[7], Ofer Benjaminov MD[7], Gil N Bachar MD[8], Shlomit Tamir MD[8], Yael Rapson MD[8], Dror Suhami MD[8], Amiel A Dror MD PhD[6], Naama R Bogot MD[7], Ahuva Grubstein MD[8], Nogah Shabshin MD[5], Yishai M Elyada PhD[9], Yonina C Eldar PhD[3]

Step 1: Pre-processing + Segmentation



Step 2: Deep learning algorithm





COVID19 Task Force

- Collaboration with Prof. Libertario Demi et. al
- COVID19 detection from LUS + severity grading
- Based on model-based features
- Close to 80% detection

מכון ויצמן למדע
WEIZMANN INSTITUTE OF SCIENCE

THE HEBREW UNIVERSITY OF JERUSALEM

ULTRa
ULTRASOUND LAB TRENTO

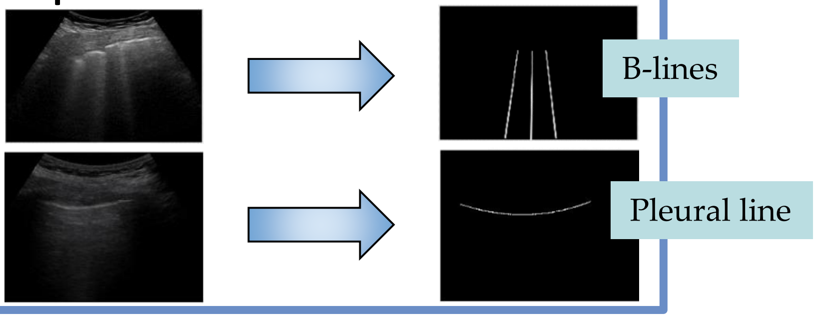
Sackler Faculty of Medicine
Tel Aviv University

Fondazione IRCCS
Policlinico San Matteo

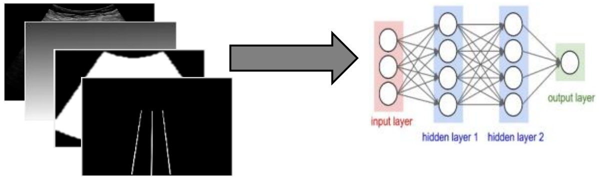
Gemelli

Brescia MEd

Step 1: Line Detection



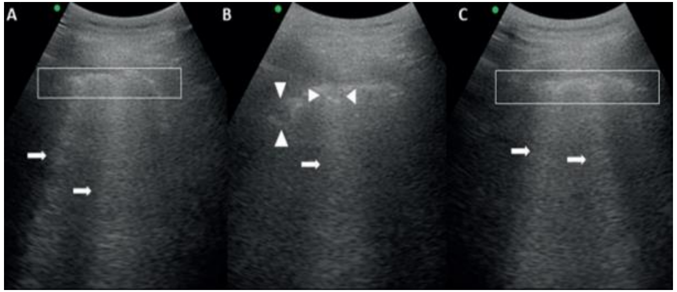
Step 2: Deep learning algorithm



IEEE TRANSACTIONS ON MEDICAL IMAGING, PREPRINT – UNDER REVIEW

A Framework for Integrating Domain Knowledge into Deep Networks for Lung Ultrasound, and its Applications to COVID-19

Oz Frank, Nir Schipper, Mordehay Vaturi, Gino Soldati, Andrea Smargiassi, Riccardo Inchingolo, Tiziano Perrone, Federico Mento, Libertario Demi, *Member, IEEE*, Meirav Galun, Yonina C. Eldar, *Fellow, IEEE*, and Shai Bagon



Efficient, Interpretable, High Resolution Sensing: Results and Vision

To learn more from less data we must take advantage of all the information possible!

Exploit structure and goal in model based and data driven methods

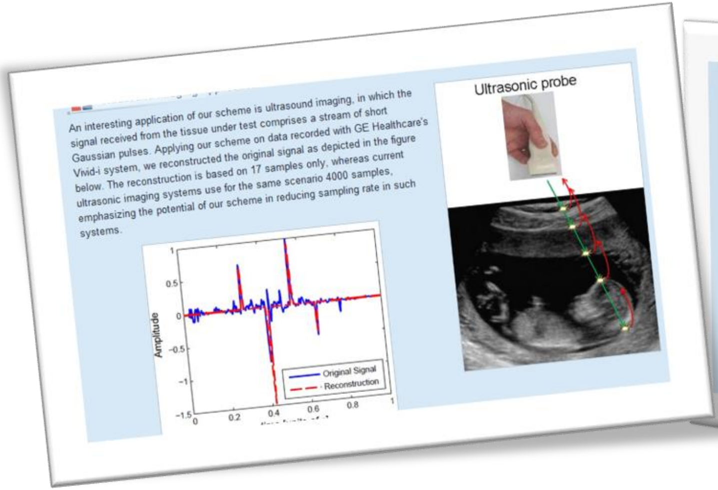
Mathematical limits:
Sampling rates
Coding rates
Superresolution limits

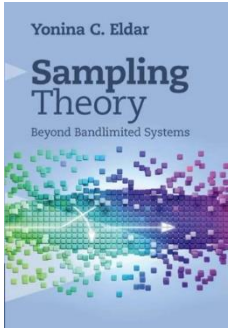
Engineering Research:
Development of new samplers
Technological applications
that break existing barriers

Scientific/clinical breakthroughs:
Thanks to the possibility of
seeing what we could
not see before ...

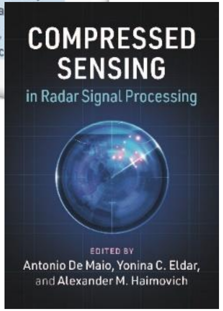
Visit Our Webpage

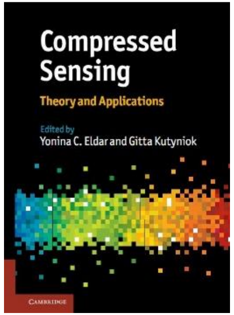
Y. C. Eldar, “Sampling Theory: Beyond Bandlimited Systems", Cambridge University Press, 2015





Y. C. Eldar and G. Kutyniok, "Compressed Sensing: Theory and Applications", Cambridge University Press, 2012
A. D. Maio, Y. C. Eldar and A. M. Haimovich, "Compressed Sensing in Radar Signal Processing", Cambridge University Press, 2019





http://www.wisdom.weizmann.ac.il/~yonina/YoninaEldar

SAMPL Team

If you want to go fast go alone
If you want to go far bring others

Collaborators (Partial…)


Miguel Rodrigues


Andrea Goldsmith


David Smith


Alon Kipnis


Shai Tejman-Yarden


Ruud Van Sloun

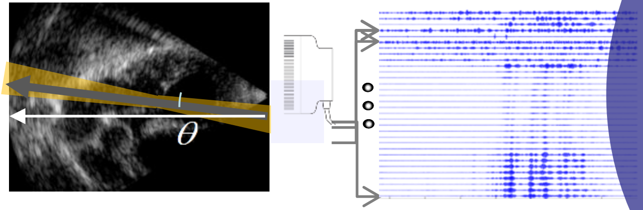

Vishal Monga

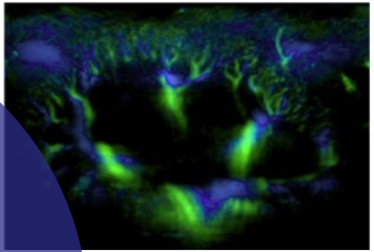

Nir Shlezinger

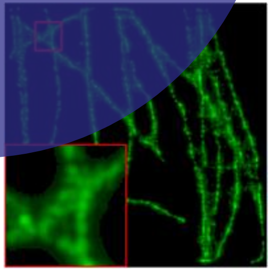

Tianyao Huang


Geert Leus

Thank You!







If you found this interesting …
Looking for graduate students and post-docs!