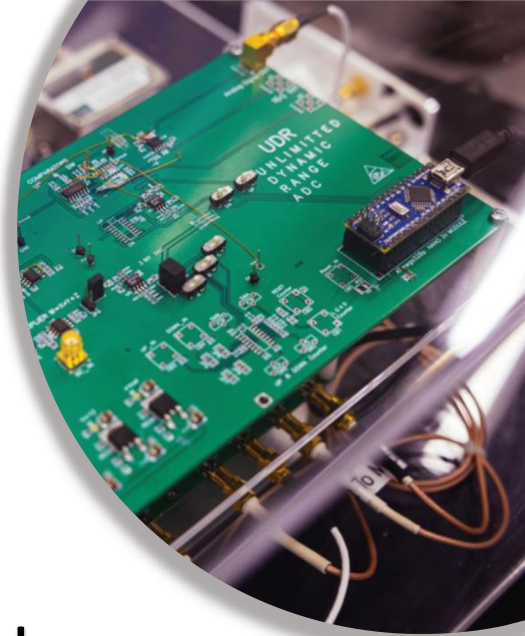


TRANSLATIONAL AI and ENGINEERING in Health and Communication

December 27, 2022

SAMPLLAB
Signal Acquisition Modeling Processing and Learning

The Days of AI and Big Data…

KE Write a poem William Shakespeare style about the "Translational AI and Engineering in Health and Communication" workshop, taking place at the Weizmann Institute of Science.

In this age of science and technology,
Where the boundaries of knowledge are pushed with dexterity,
A workshop is taking place, a sight to see,
Translational AI and engineering, at the Weizmann Institute.

At this hallowed hall, where minds converge,
Experts in their field, with knowledge to purge,
Will gather to discuss and share their knowledge and treasure,
On the intersection of AI, engineering, and health, a measure.

No longer will we be left in the dark,
About the power of AI, and its potential to spark,
Innovation and progress, in health and communication,
At the Weizmann Institute, a new era is born, with determination.

So let us praise this workshop of note,
And give thanks for the knowledge it will promote,
For with its help, we can move forward,
Towards a brighter future, with AI as our ward.

How far AI has come… Can we utilize it for truly important purposes?

Translational Research in Signal Processing and AI

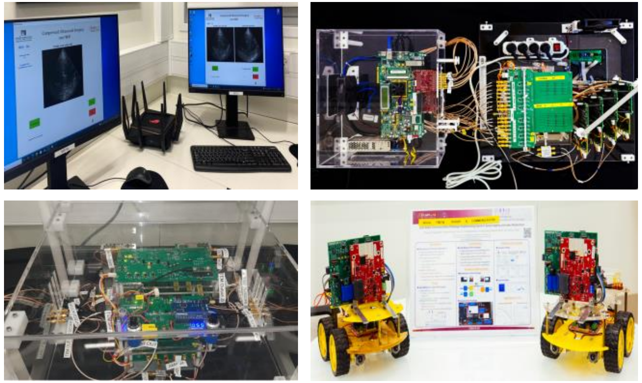
Bringing together science and technology to address real-world challenges!

Our goals from today’s workshop:

- Demonstrate how signal processing and AI can advance applications in different arenas (health, communication, automotive, radar, etc.)
- Inspire new collaborations between academy, healthcare community and industry
- Think how we can leverage the advantages of academia and industry to make a true impact on unmet needs

Agenda

- **SESSION 1:** TECHNOLOGIES IN THE ERA OF BIG DATA
- **SESSION 2:** AI AND TECH FOR HEALTHCARE
- **SESSION 3:** COMMUNICATION AND RADAR
- **ROUND TABLE DISCUSSION**
- **DEMO EXHIBITION**



Thank You!

- SAMPL lab members
- Our collaborators from the hospitals, industry and academy
- Weizmann conferences section
- Our speakers: Prof. Irit Sagi, Shmuel Auster, Prof. Eli Konen, Dr. Efrat Shema, Dr. Leeat Keren, Dr. Nir Shlezinger, Assaf Touboul
- Our supporters along the years

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

הקרן הלאומית למדע

Yad Hanadiv ياد هَنَديف יד הנדיב

רשות החדשנות
Israel Innovation Authority

IPMP
תכנית מחקר ברפואה ממוקדת אישית
برنامج الطب الشخصي
Israel Precision Medicine Partnership

erc

Introducing SAMPL Lab and The Center for Biomedical Engineering

Yonina Eldar

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Center for Biomedical Engineering and Signal Processing | Department of Mathematics and Computer Science | Weizmann Institute of Science

WEIZMANN INSTITUTE OF SCIENCE

TRANSLATIONAL AI and ENGINEERING
in Health and Communication

SAMPLLAB
Signal Acquisition Modeling Processing and Learning

The Manya Igel Center for Biomedical Engineering and Signal Processing

Where engineering, science and medicine meet

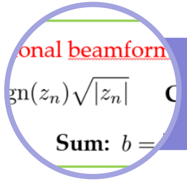
Translational AI and Engineering Research in Health, Sensing and Communication






The 4 Pillars of Our Center

Center for Biomedical Engineering and Signal Processing



Theoretical research

SAMPL lab

Clinical arm

Between Science and Technology (BeST) Forum

SAMPL Lab: Signal Acquisition Modeling Processing and Learning

The technology pillar of our center:

Develop innovative methods for signal acquisition, processing, and learning

Transform theory into real prototypes in various fields including: communication, Radar, medical and optical imaging, biological inference

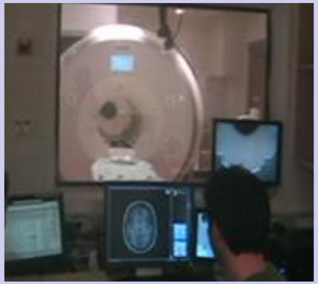
Collaborate with industry partners via our **technology forum** to advance next-generation technologies



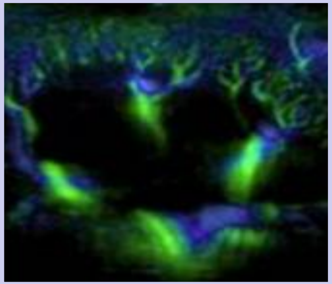

SAMPL Lab: Signal Acquisition Modeling Processing and Learning

TECHNOLOGIES

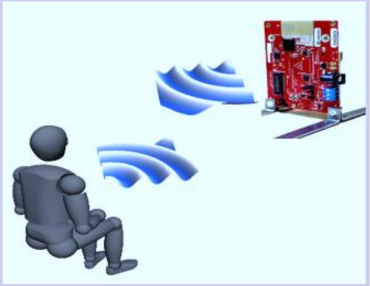
Help make technologies more powerful and more accessible to everyone



Fast and quantitative MRI

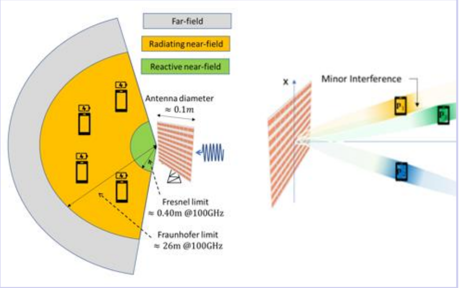


Super-resolution microscopy



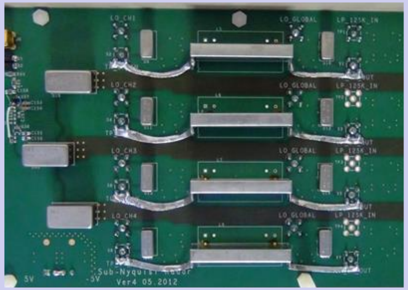
Remote sensing

Wireless ultrasound



6G communication systems

Joint radar-communication system



High resolution radar

SAMPL Lab - Major Topics of Research

Radar & Communication

- MIMO communication & radar systems
- Sparse arrays for automotive radar
- Radar and sensors for health applications
- Joint radar-communication for automotive
- Smart antenna design for ultrasound, radar and comm
- Super resolution and efficient radar systems
- 6G comm: near field, RIS, ISAC..

Smart Sampling

- Level-Crossing sampling & time encoding machine (TEM)
- Modulo sampling & automatic gain control
- Task based sampling
- Sub-Nyquist sampling

Machine Learning

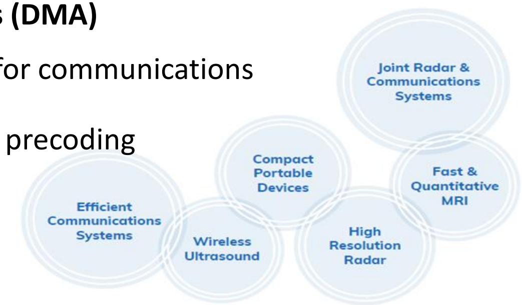
- AI for COVID19 detection & monitoring
- AI for clinical applications
- Model-based machine learning
- Machine learning for wireless communications

Ultrasound Technologies

- Super resolution in ultrasound imaging
- Compressed beamforming for wireless ultrasound imaging

Dynamic Metasurface Antennas (DMA)

- Metasurfaces antennas for communications
- Metasurfaces for analog precoding



SAMPL Clinical

The infrastructure for clinical research:

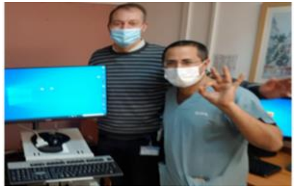
SAMPLLAB CLINICAL

Brainstorm with leading physicians via our unique **Clinical Forum**

Identify unmet medical needs and important research topics

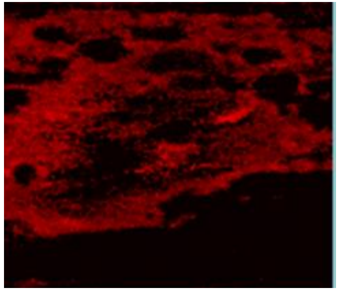
Design clinical studies that address these needs, in collaboration with physicians from Israel and abroad

Harness Innovations in signal processing and artificial intelligence for the welfare of patients worldwide!

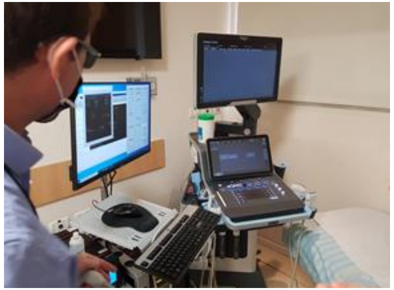



SAMPL Clinical

Bringing the bench to the bedside and back!

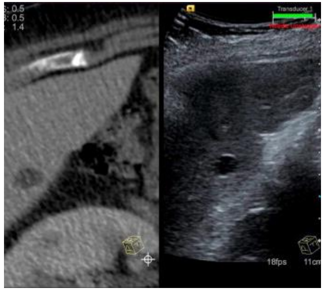


Super-Resolution for Ultrasound



Ultrasound Channel Data

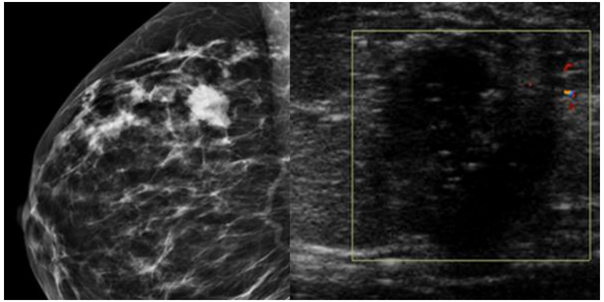
AI-Guided Ultrasound Image Acquisition



AI Conversion between Modalities

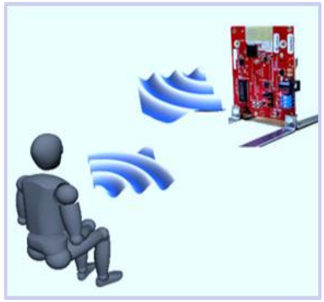
Wearable Devices

POCUS/Lung Ultrasound



Combining Imaging Modalities Using AI

Covid-19



Radar for Clinical Applications

Various Clinical Collaborators – in Israel and Abroad!

SHEBA
Tel HaShomer
City of Health

NYU Langone
MEDICAL CENTER

RAMBAM
Health Care Campus

MASSACHUSETTS
GENERAL HOSPITAL

מרכז שניידר לרפואת ילדים בישראל
مركز شنايدر لطب الأطفال في اسر ائيل
Schneider Children's Medical Center of Israel

המרכז הרפואי
שערי צדק
SHAARE ZEDEK
MEDICAL CENTER

מרכז רפואי העמק
רפואה מתקדמת בדיוק בשבילך

RABIN MEDICAL CENTER
BEILINSON • HASHARON

Memorial Sloan Kettering
Cancer Center

Examples of Clinical Collaborations:

RABIN MEDICAL CENTER BEILINSON • HASHARON	Improving breast cancer diagnosis using super-resolution and multi-modal machine learning
RABIN MEDICAL CENTER BEILINSON • HASHARON	Improving Crohn's disease diagnosis and monitoring using super-resolution ultrasound
מרכז שניידר לרפואת ילדים בישראל / مركز شنايدر لطب الأطفال في اسرائيل / Schneider Children's Medical Center of Israel	AI-guided image acquisition to enhance imaging of ovaries in pediatric patients
מרכז רפואי העמק	Improving the diagnosis of pleural diseases using ultrasound channel data and machine learning
המרכז הרפואי שערי צדק / SHAARE ZEDEK MEDICAL CENTER	Improving monitoring of Gaucher's disease using machine learning
NYU Langone MEDICAL CENTER	Machine learning and ultrasound channel data to enhance diagnosis of chronic liver diseases
Memorial Sloan Kettering Cancer Center	Machine learning approach to sonographic assessment of tumor volumes for response assessment in patients with pancreatic cancer

And many more, including a joint Covid-19 study with several hospitals

Efficient Data Processing for Enhanced Technologies

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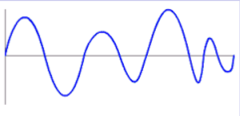
Signal Acquisition Modeling Processing and Learning

Digital Revolution

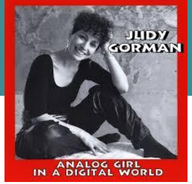
- Processing of physical data by computers and digital devices
- Digital devices store and process strings of bits, namely, 0s and 1s
- Data processing: mathematical algorithms performed on the bits



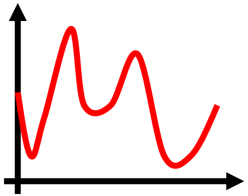
01001001001010010...

01001001001010001101111
0100101101011001...

“Analog Girl in a Digital World…” Judy Gorman 99



Analog world

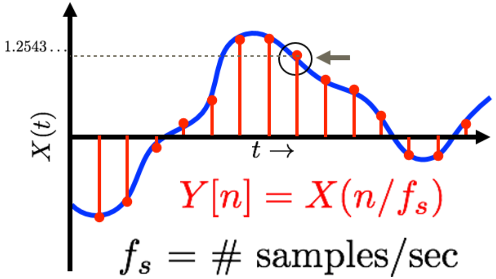


$x(t)$

- Music
- Radar
- Communication
- Image…

Sampling

Analog-to-Digital Convertor (ADC)



$$Y[n] = X(n/f_s)$$

$$f_s = \#\ \text{samples/sec}$$

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

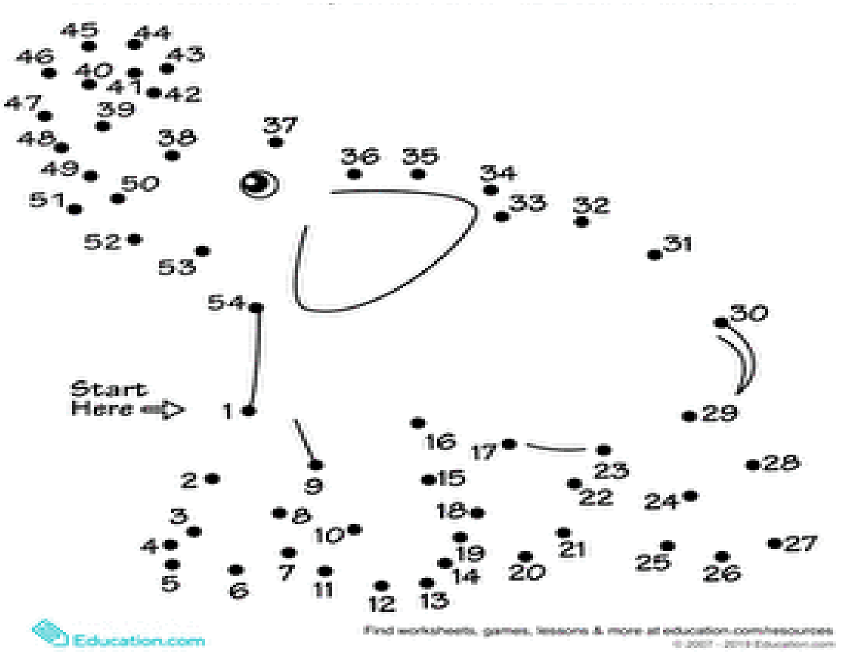
Digital world

$y[n]$ 010010110

- Signal processing
- Image denoising
- Compression…

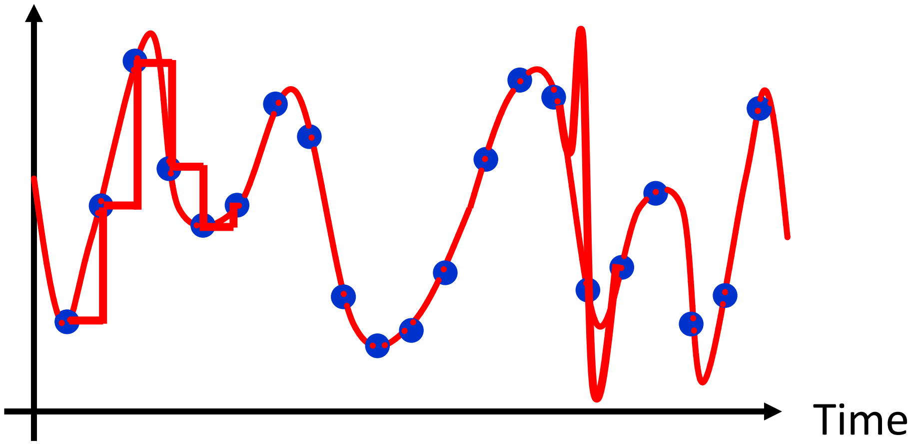
Sampling Recovery

$x(t)$ → **Sampling Analog-to-Digital (ADC)** → $y[n]$



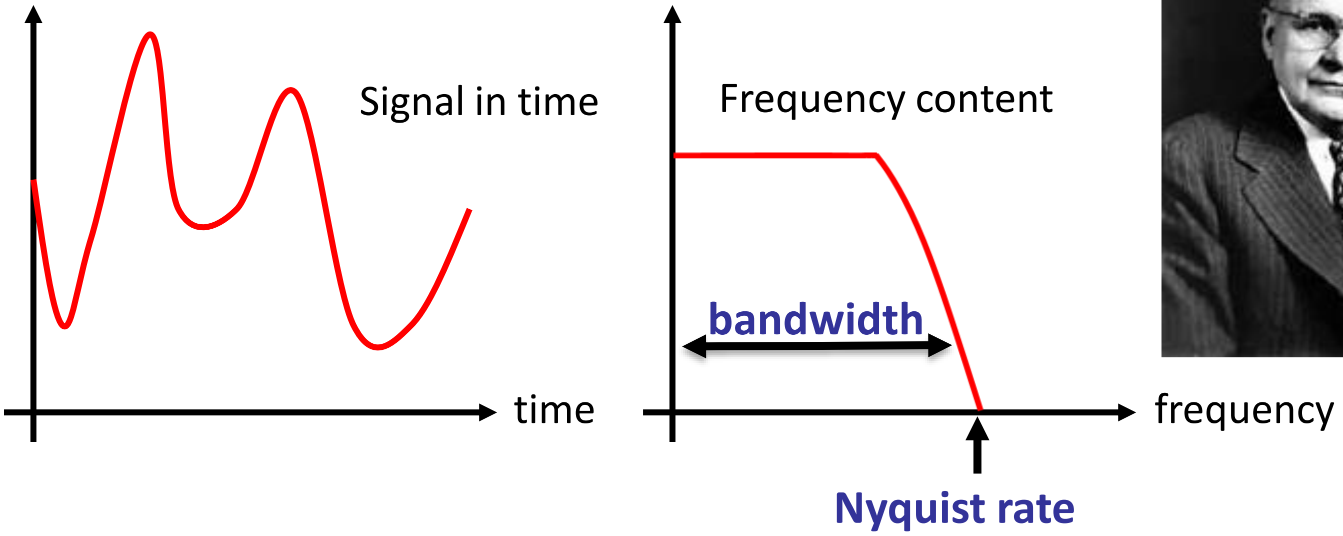
Sampling Recovery

$x(t)$ → **Sampling Analog-to-Digital (ADC)** → $y[n]$



Need to limit the speed of change!

Nyquist Theorem (1928) Recovery



$$x(t) = \sum_{n=-\infty}^{\infty} x(nT)\mathrm{sinc}(t - nT), \quad T = \frac{1}{f_s}$$

Sampling rate must be greater (or equal)
than twice the **maximal** frequency of the signal

Shannon Theorem (1948)

> Maximum amount of information that can be sent over a channel:

$$C \approx W \times n \times \log_2(1+SNR)$$

Capacity — Total data throughput capacity of the system

Spectrum — Radio frequency spectrum utilized by the network

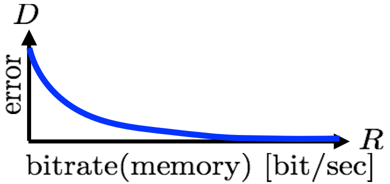
Antennas — Number of antennas on uncorrelated signal paths

Signal Quality — Signal to Noise Ratio on the communication channel

> Minimal compression distortion using a fixed number of bits

$$R(D^*) = \frac{1}{2}\log\left(\frac{\sigma^2}{D^*}\right)$$

$$y[n] \longrightarrow \boxed{\text{ENC}} \longrightarrow \boxed{\text{DEC}} \longrightarrow \hat{y}[n]$$

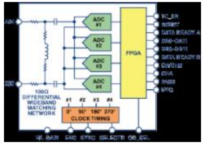


Challenges of Nyquist and Shannon Bounds

Large Bandwidth

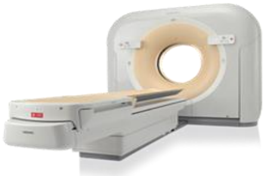
- High rate communications
- High resolution e.g. in radar and imaging

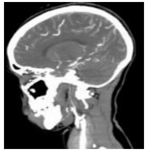
High rate samplers and quantizers



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

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

Physical Bounds: Super Resolution

> All measuring devices are bandwidth or resolution limited due to diffraction

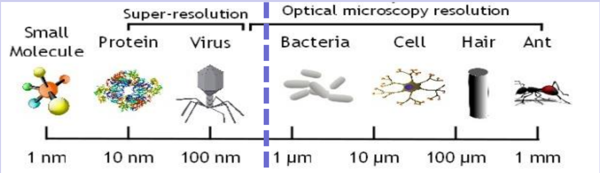
> Diffraction: spreading of waves passing through an aperture

> Abbe's diffraction limit in optical imaging:

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

Spatial resolution is proportional to half the imaging wavelength

Diffraction Limit



> Spatial resolution in an antenna array or ultrasound probe is inversely proportional to the aperture

Science and Math Lead to Bounds on Technology!

The Technology Future: Defeating Physics & Math by Combining Them!

Science imposes limits on our ability to hear, see and communicate

+

Mathematical analysis imposes limits on technology in terms of speed, size, and power

→

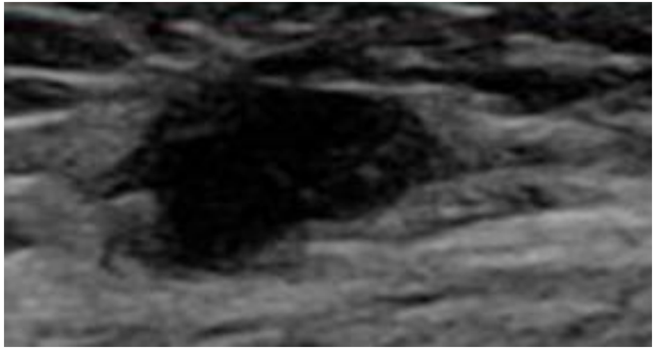
Synergize the two:
Use physics to enable new ways of conveying information that can only be interpreted by mathematical algorithms
- to enable new technologies!

IF YOU CAN'T BEAT THEM **JOIN THEM**

Contrast Enhanced Ultrasound

> Ultrasound is wave-based and therefore resolution limited

> Physics: Use contrast agents (Sonovue)



Sonovue contains gas microbubbles poorly soluble in aqueous solutions

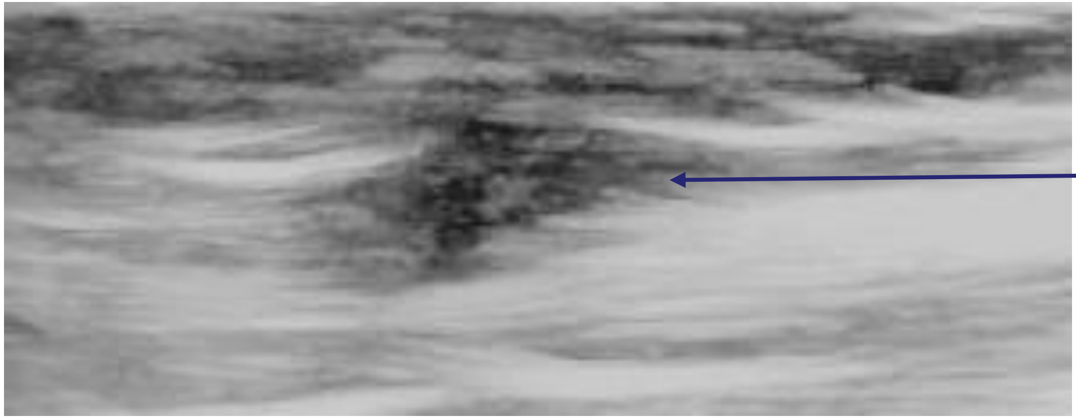
The interface between the bubbles and blood acts as a reflector of the ultrasound beam

↑ blood echogenicity

↑ contrast between the blood and the surrounding tissues

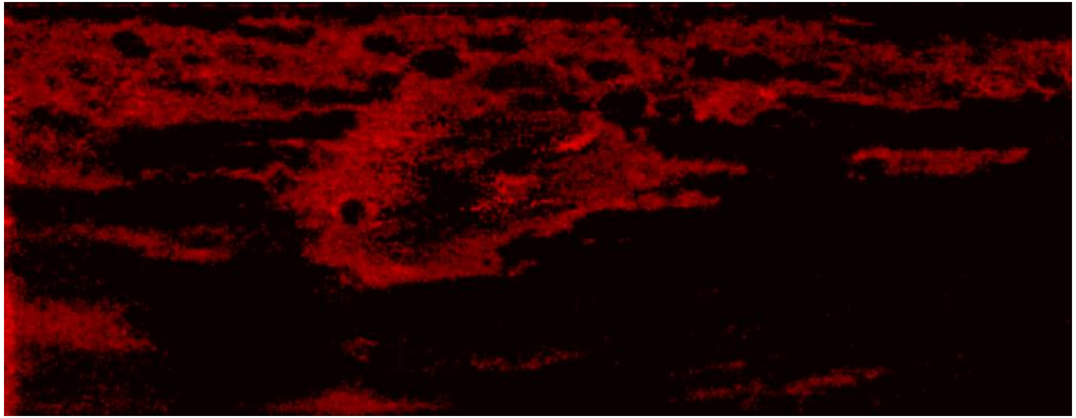
Super Resolution Using CEUS

This does not always work – sometimes contrast only makes everything brighter!



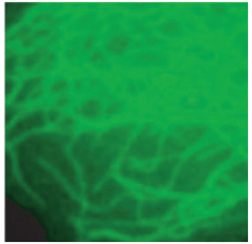
Difficult to separate lesion from tissue

Combine math and physics: Track bubbles to get super resolution!



Florescence Microscopy

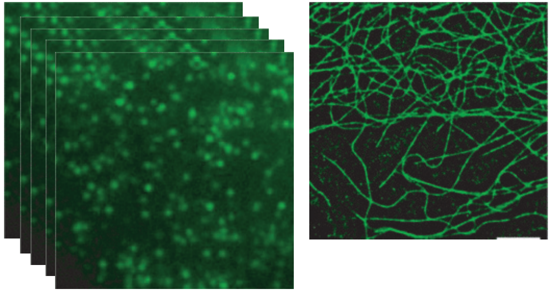
Standard optical images are resolution limited



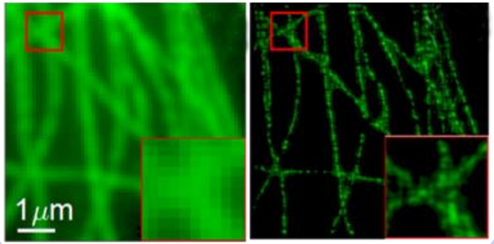
Noble prize 2014:

Super resolution florescence microscopy

Injecting fluorophores can increase resolution 10 fold but precludes live cell imaging



Increase fluorophore density and use algorithms to localize!

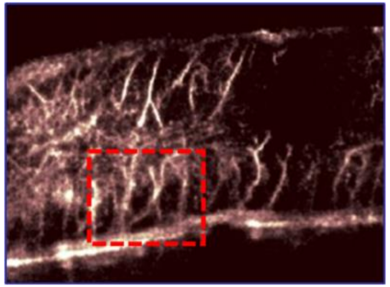


Cross-Fertilization of Science and Technology

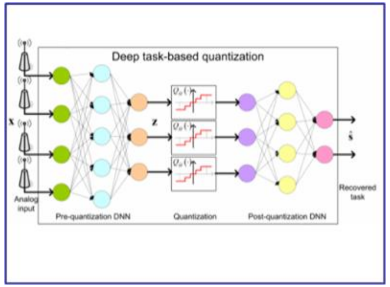
Moving to technology inspires new ways of transmitting signals and new mathematical and physical limits to investigate

New physics and algorithms inspire new technologies

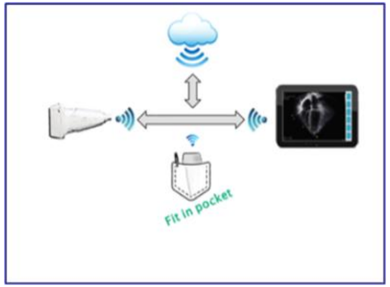
… Science advancing technology, advancing science…



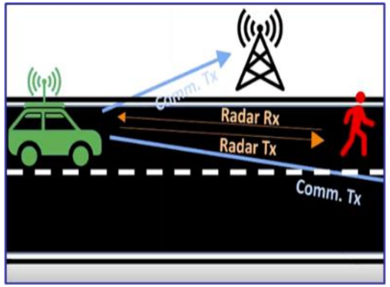
Super-resolution ultrasound



Efficient quantizer



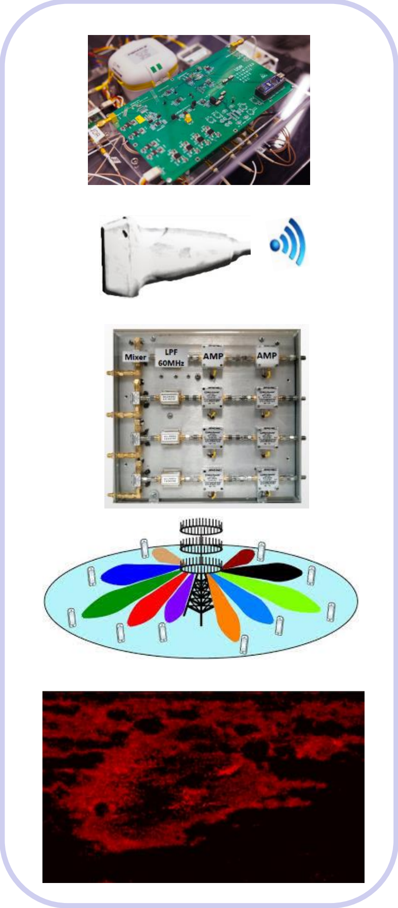
Portable ultrasound probe

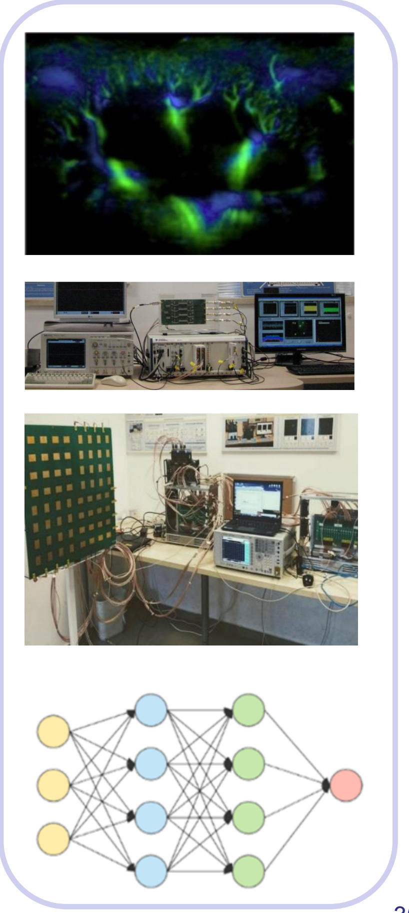


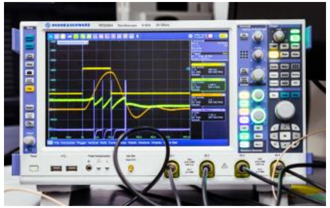
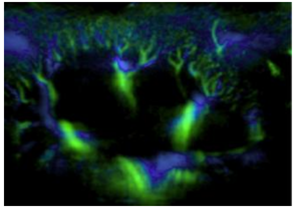
Automotive joint radar-communication

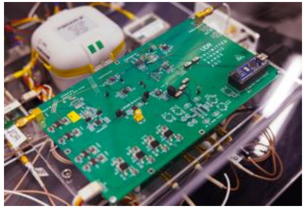
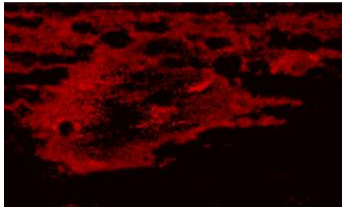
Talk Outline

- PACE Technology: Physics and Algorithms Coupled to Enhance technology
- Applications to ultrasound and radar
- Super resolution in microscopy and US
- Model-based artificial intelligence





PACE Technology

Physics and Algorithms Coupled to Enhance Technology

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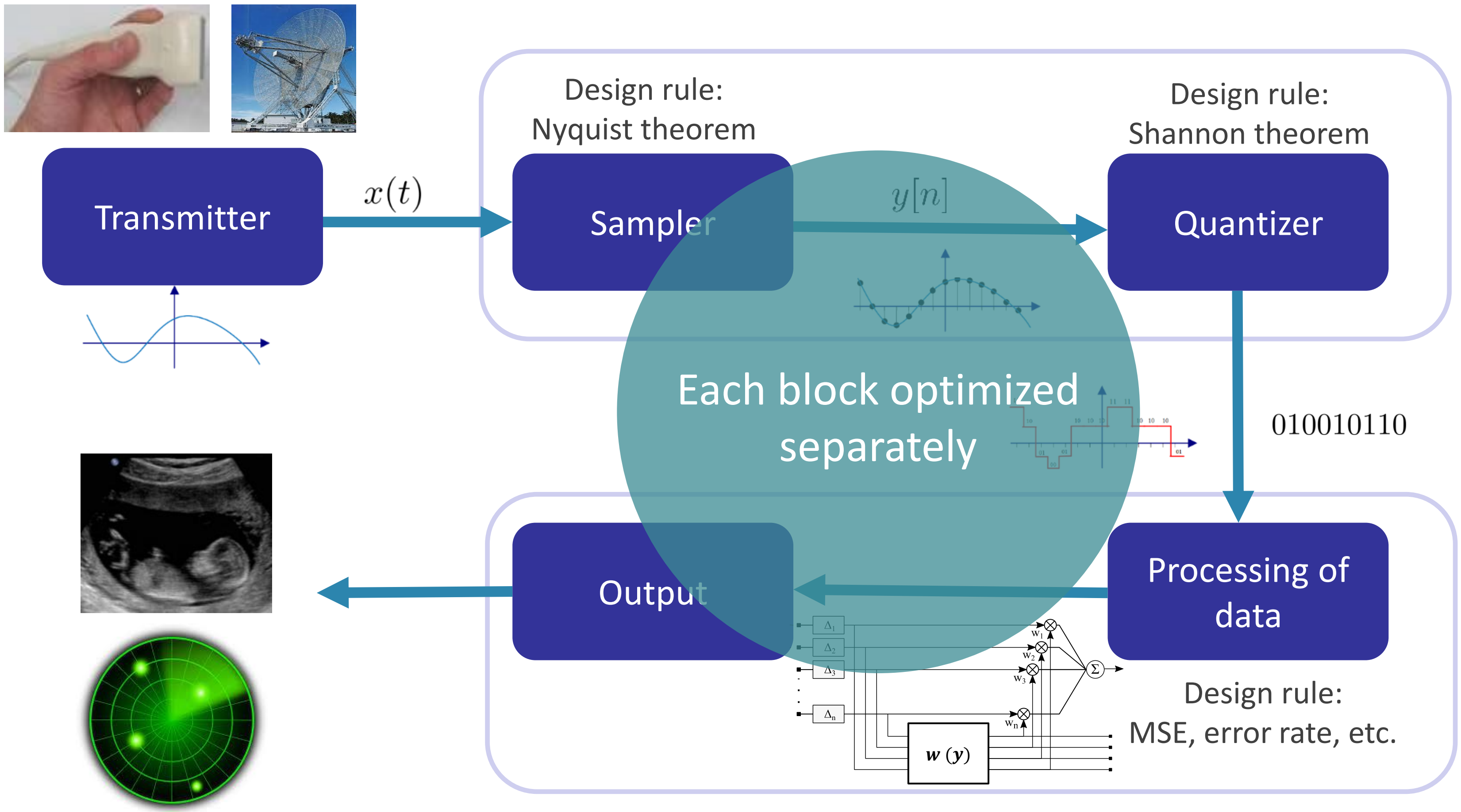
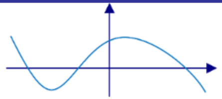
Signal Acquisition Modeling Processing and Learning

Standard Acquisition Systems: Modular Design



Joint PACE Acquisition Systems

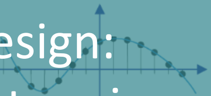
Transmitter



$x(t)$

Sampler

$y[n]$



Quantizer

010010110

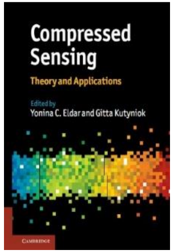
Joint Design:

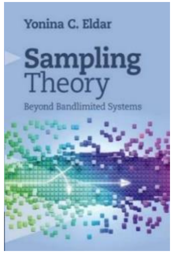
- Structure in input/system
- Output task
- Math recovery

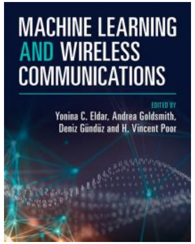
Processing of data

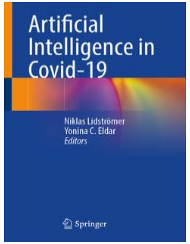
Output

Model based, efficient, and interpretable data driven methods!



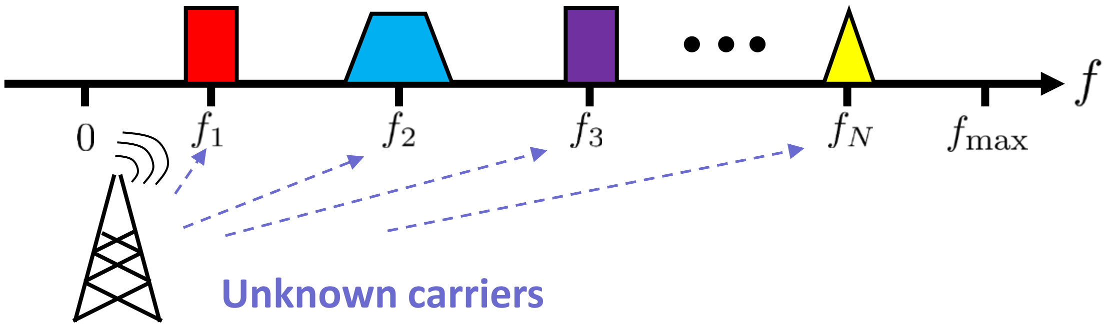




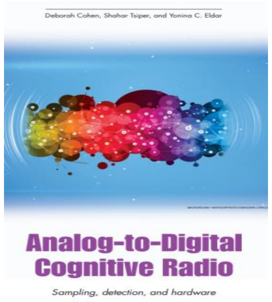


Multiple Frequency Bands

> Multiband Communication

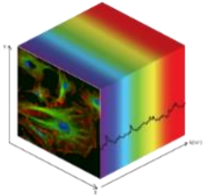


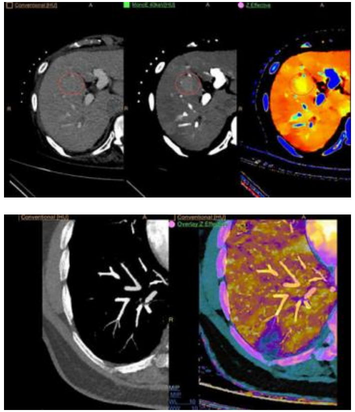
> Mishali and Eldar 09



- 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

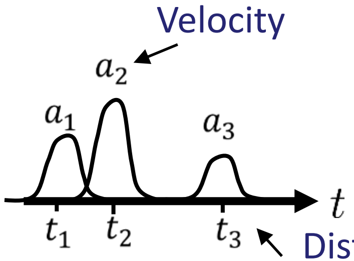


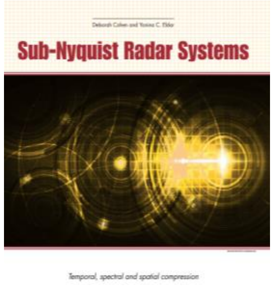


Streams of Pulses

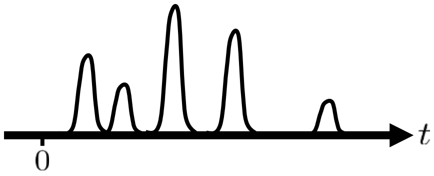
> Vetterli et. al, 02

Radar:





Ultrasound:

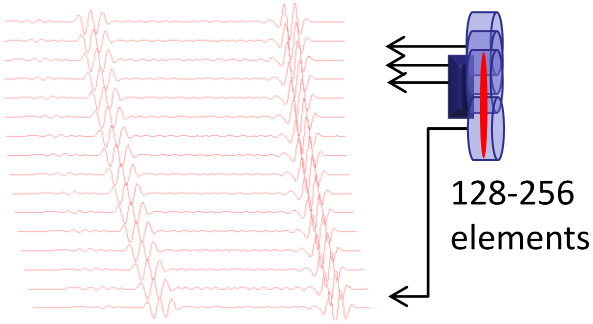


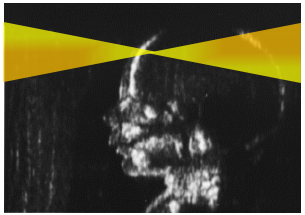
A sampler that takes advantage of the pulses' structure can use fewer samples and lead to higher resolution

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





Scan Plane

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!

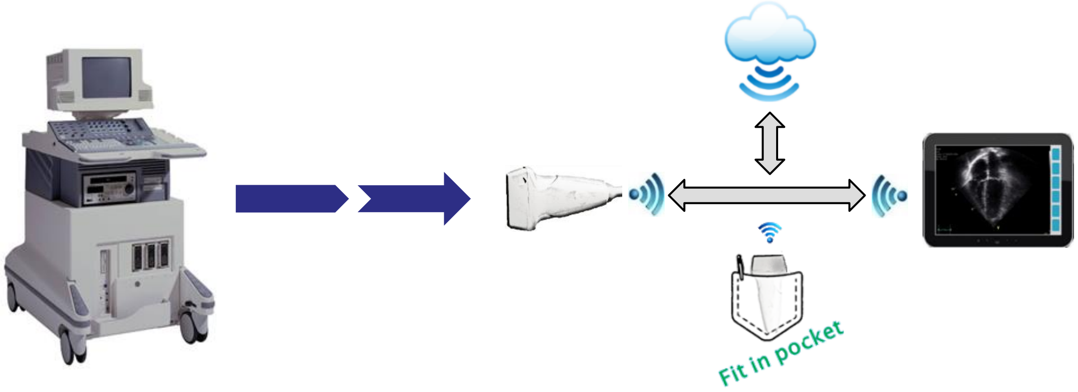
Challenges

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



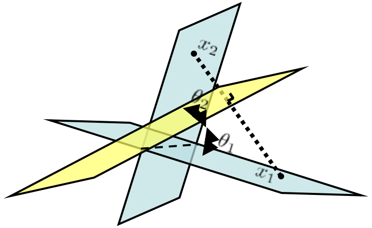
Union of Subspaces

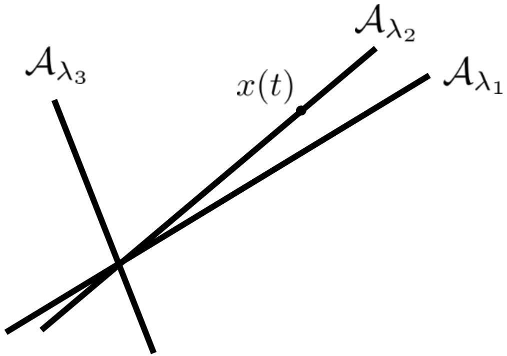
> Lu and Do 08, Mishali and Eldar 09

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

$x(t) \in \mathcal{A}_{\lambda^*}$ $\rightarrow$ λ^* 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

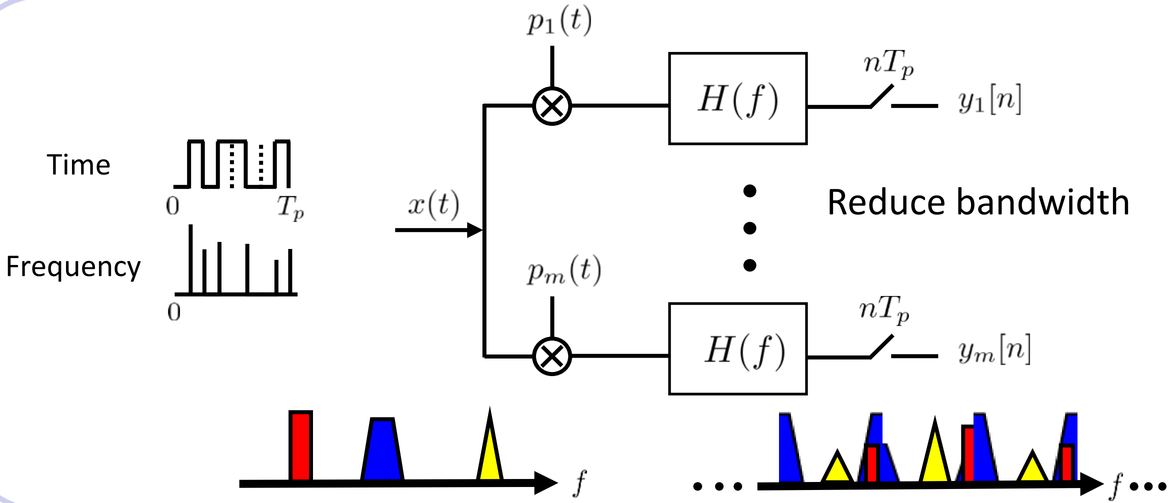
A sampling operator is invertible over a union of subspaces $\mathcal{U}$ if and only if it is invertible for every

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

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

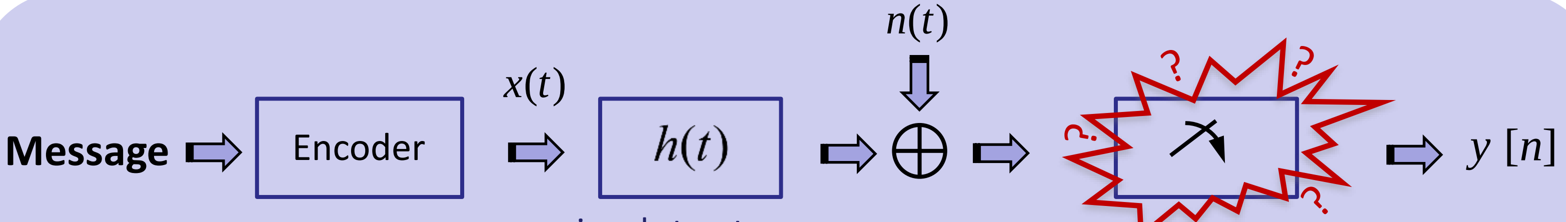
x(t) ⇨  ⇨ Acquisition ⇨ Compressed sensing and processing ⇨ recovery

Analog preprocessing — Low rate (bandwidth)

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

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

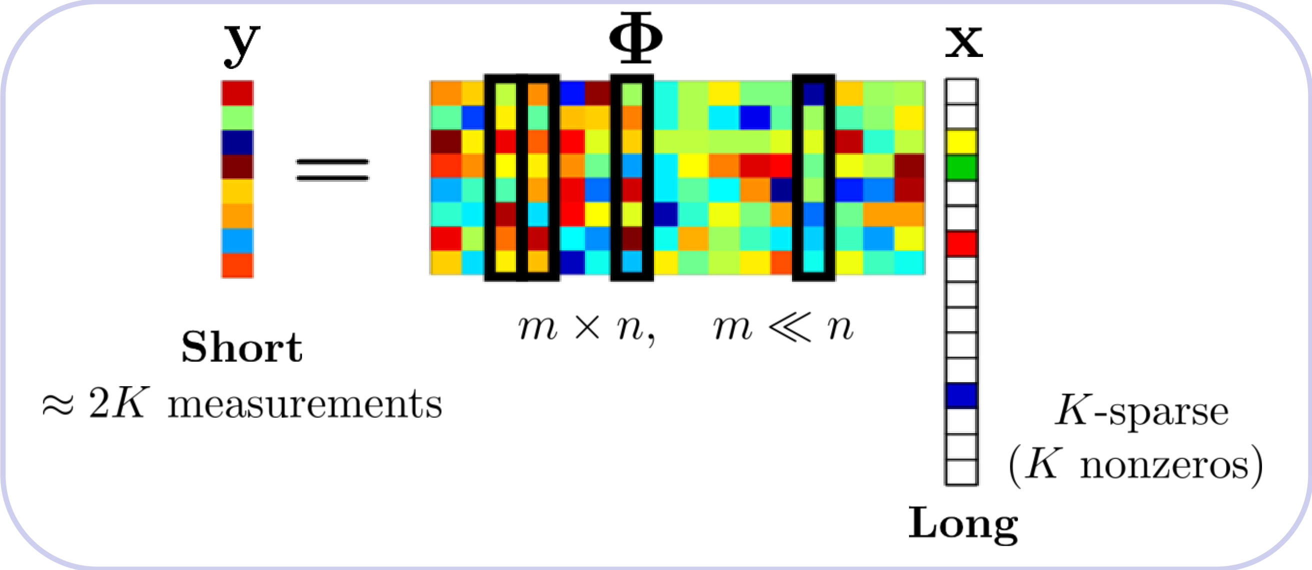
$$\mathcal{H}(\beta) = -\beta\log\beta - (1-\beta)\log(1-\beta)$$

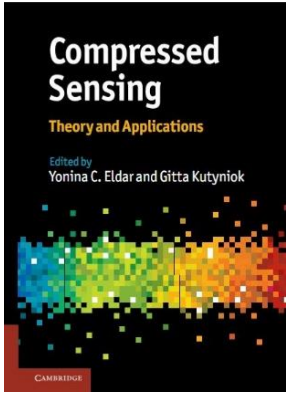
binary entropy function

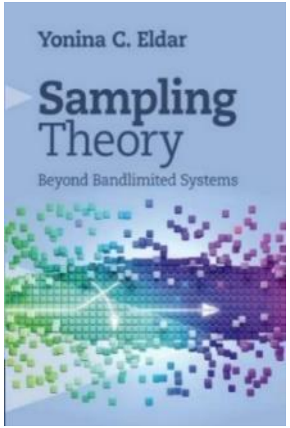
- α: undersampling factor
- β: sparsity ratio

Compressed Sensing

> Candes, Romberg, Tau 06, Donoho 06







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

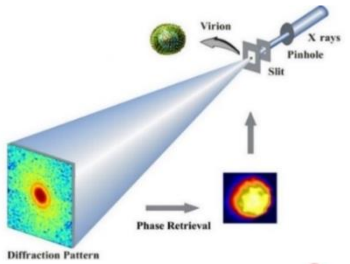
> Nonlinear sparse recovery (optics):
  - Phase retrieval
    (Shechtman et. al 11, 14, 15, Eldar and Mendelson 12, Ohlsson et. al 12)
  - Nonlinear compressed sensing
    (Beck and Eldar 12, Bahman et. al 11, Ohlsson et. al 13, Yang et. al 15)

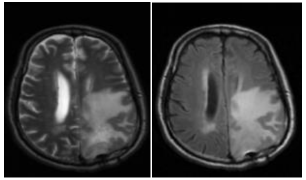
> Reference based sparse recovery (MRI)
(Weizman, Eldar and Ben Bashat 16)

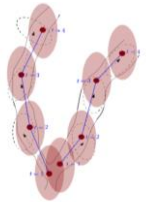
> Sparsity with tracking (ultrasound) (Solomon et. al 18)

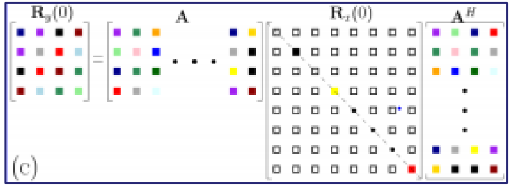
> Statistical sparsity
(Pal and Vaidyanathan 14, Solomon et. al 18, Cohen and Eldar 18, Romero et. al 16)

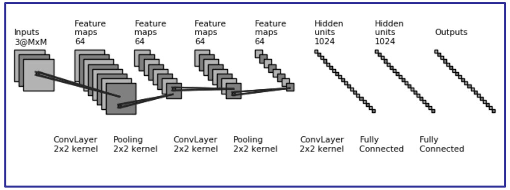
> Deep learning (Gregor and LeCun 10, Mousavi and Baraniuk 17, Borgerding et. al 17, Aggarwal et. al 18, Bora et. al 17, Wu et. al 19)





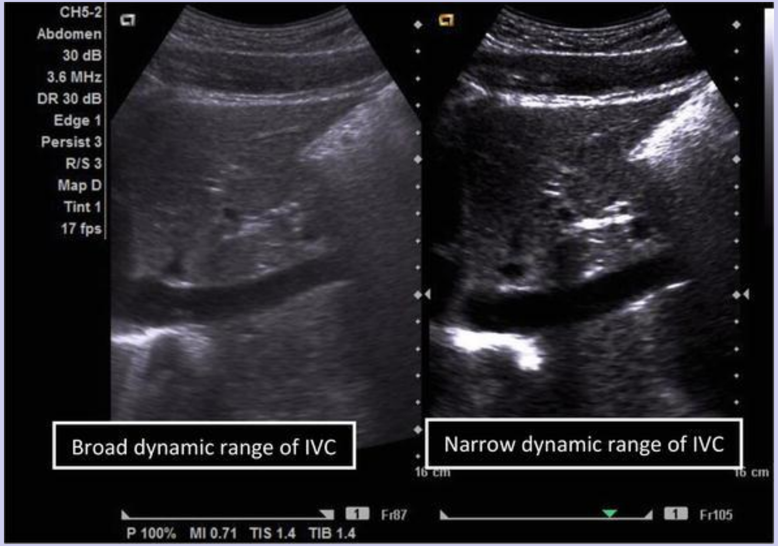






Mathematical Recovery: Dynamic Range

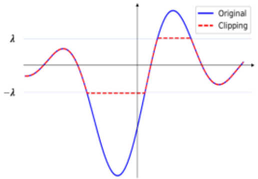
- **Dynamic range** is defined as the difference between the maximum and minimum values of the displayed signal
- Signals beyond dynamic range are clipped!
- An example of a narrow vs. broad dynamic range in an ultrasound scan:



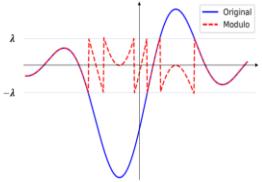
Mathematical Recovery: Dynamic Range

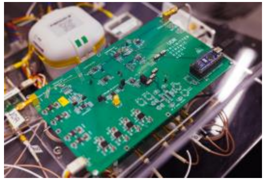
- Transmission medium or processing devices have limited dynamic range
- Clipping beyond dynamic range
- A modulo operation is used to limit dynamic range prior to transmission
- The non-linear modulo causes distortion making inference difficult
- Signal structure e.g. correlation, sparsity, is used to recover the signal

Standard ADC



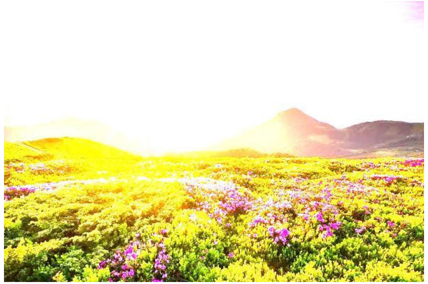
Modulo



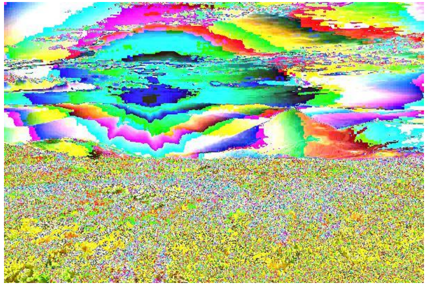


Modulo Sampler

High dynamic range image



Clipping



Folded image

Unfolded

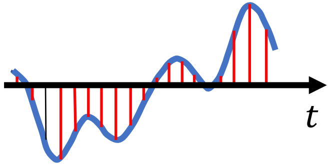
Timing Based Sensing: Efficient Hardware

Change the information recorded!

> Lazar and Toth, 04
> Adam, Scholefield, and Vetterli 20
> Naaman, Mulleti, Eldar 22

Synchronous ADC:

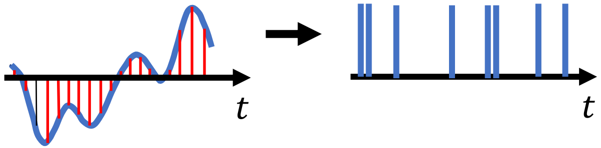
Sample signals at regular intervals
Quantizing amplitudes



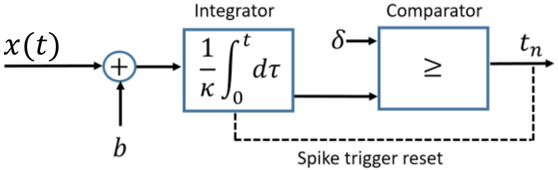
- Controlled by a global clock: Power-consuming
- Increasing the signal's amplitude
  - Increases amplitude quantization dynamic range
  - Increases required number of bits per sample

Time encoding machine:

Event-driven sensing approach
Quantizing timings



- No global clock is required: Low power consumption
- Increasing the signal's amplitude
  - Decreases timing quantization dynamic range
  - Decreases required number of bits per sample



Our hardware contains:

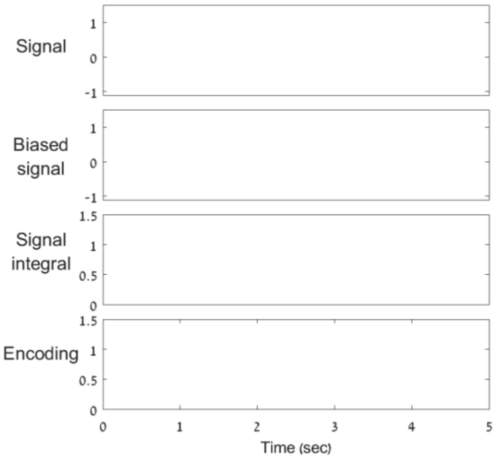
- Integrator
- Comparator
- Reset mechanism

Sampling robustly at sub-Nyquist rates!

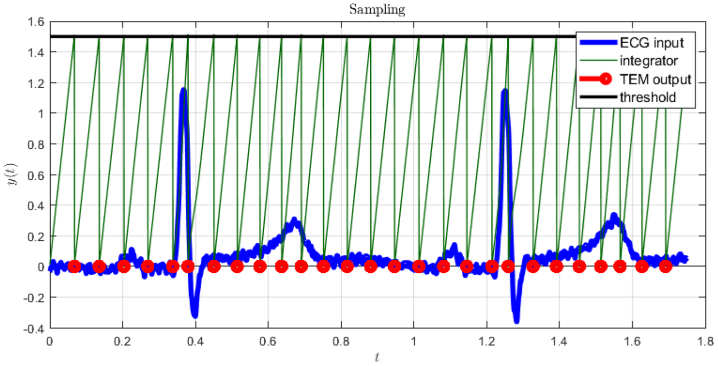
Reduce power and bits while leveraging low-cost, simple hardware

Example: ECG Continuous Monitoring

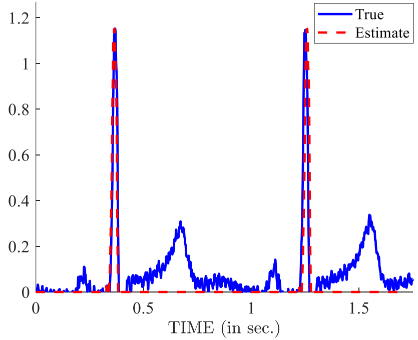
- Using synchronous ADC to extract cardiac data is consuming in power and bits
- Our sampling and recovery approach uses minimal sub-Nyquist rates with energy-efficient hardware, allowing for high-accuracy HR extraction



Hardware results in action



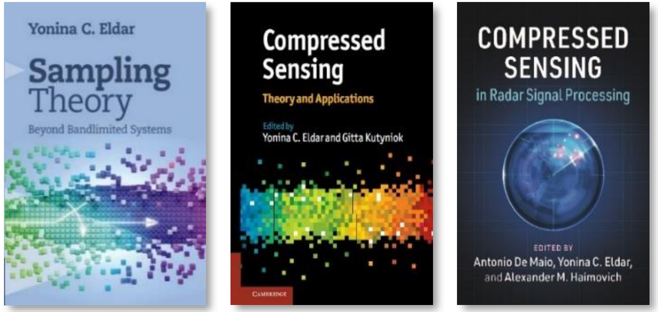
TEM sampling



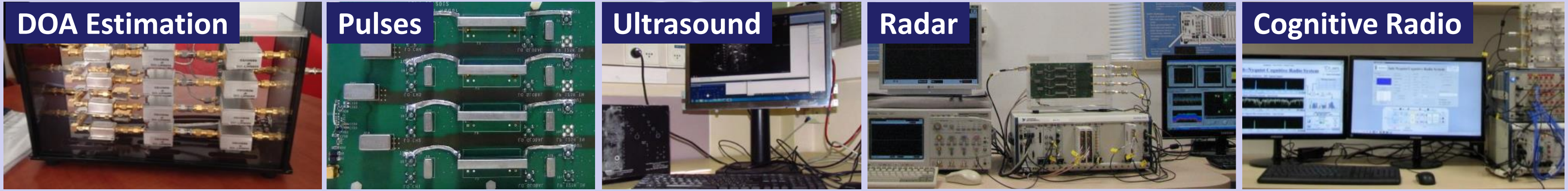
TEM Recovery

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



Two ways: theory translated to practice, building the devices led to many new theoretical concepts



Advantages of Joint PACE Design

Compact, portable devices with better imaging quality

Fast and quantitative MRI

Efficient wideband sensing

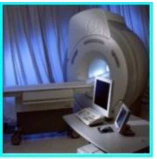
Compact, cheap and high resolution radar

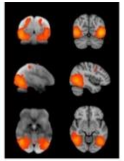
Efficient massive MIMO systems

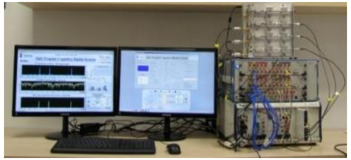
Joint radar and comm systems

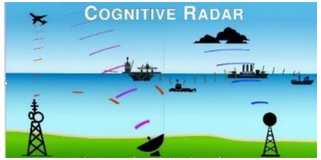
Super resolution microscopy and ultrasound

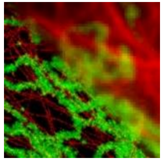
Interpretable, deep networks for medical imaging communication systems, and more

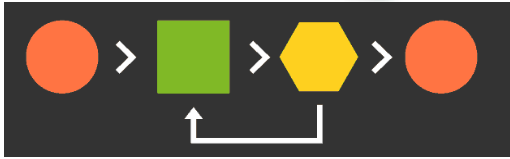




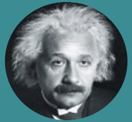








APPLICATIONS



“In theory, theory and practice are the same. In practice, they are not.” Albert Einstein

WEIZMANN INSTITUTE OF SCIENCE

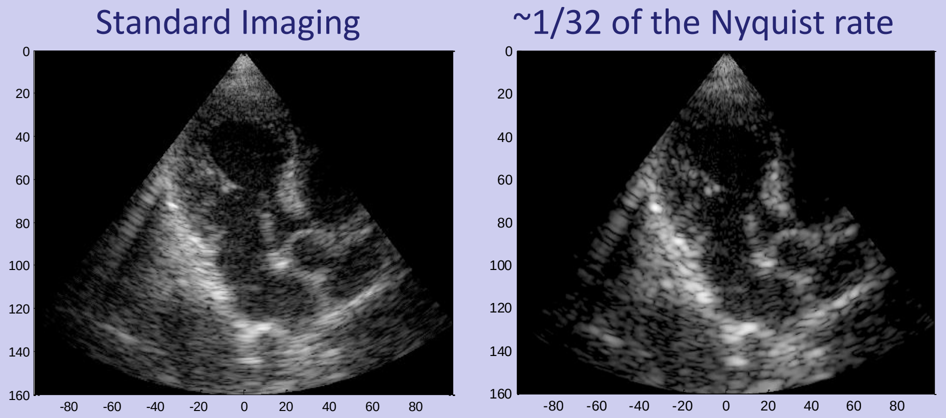
SAMPLLAB
Signal Acquisition Modeling Processing and Learning

Sub-Nyquist Ultrasound Imaging

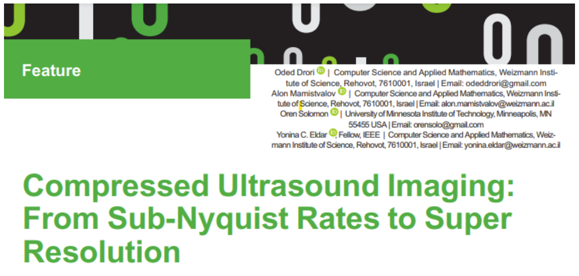
> Chernyakova and Eldar 13-15

Low rate sampling enables:

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



4% Nyquist rate at every channel!


Feature

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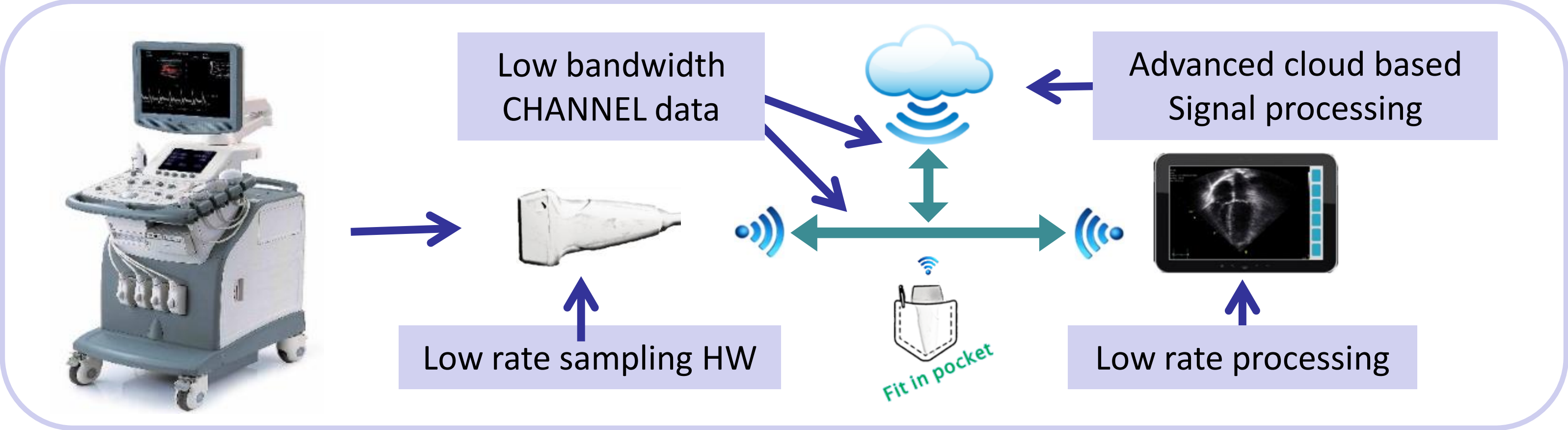
Compressed Ultrasound Imaging: From Sub-Nyquist Rates to Super Resolution

Bring the Digital Revolution to Ultrasound, Anywhere

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

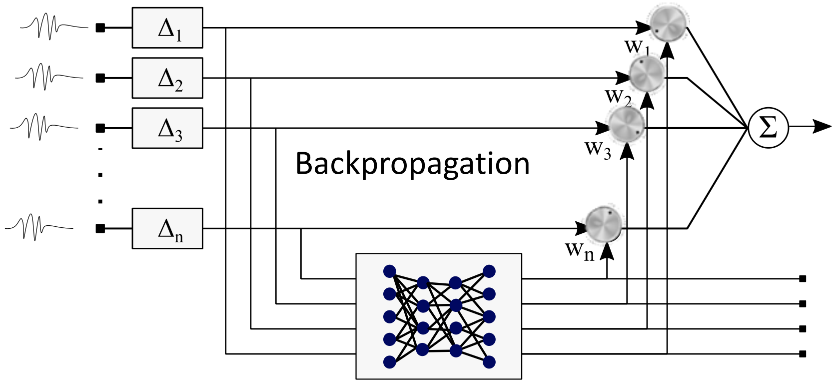
- Allows to integrate electronics into probe: wireless ultrasound
- Enabling an "open imager" – advanced signal processing and AI methods **on channel data** that can run on any platform
- Enabling remote health flexibility
- Super resolution methods



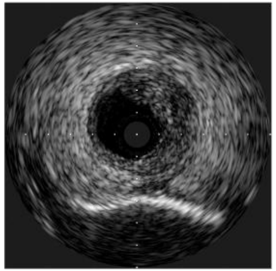
Demo Movie

Deep Adaptive Beamforming

> Luijten et. al 19

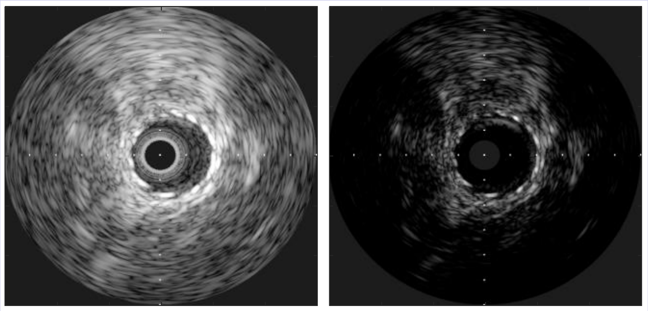


High-quality target (EBMV)



Model based: Weights determined by deep learning!

Delay-and-sum (standard)



Deep learning

Improved contrast and resolution

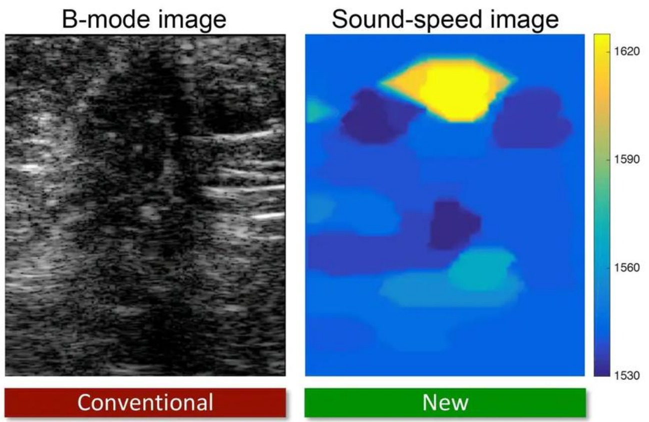
Inverse Ultrasound – Extracting Tissue Properties

> Shultzman and Eldar, 22

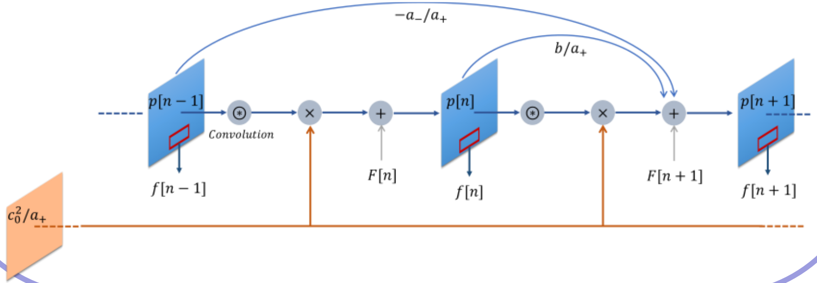
Since different tissues have different physical properties, they reflect sound waves differently
> **Speed of Sound (SoS)**
> **Acoustic attenuation**
> **Density**
> **Elasticity**

These measurements encode information about the gross structure of the tissue!
> Use wave equations to relate the data with these properties
> Backpropogate to extract properties!

The inverse method:
Acquired ultrasound signals → tissue properties



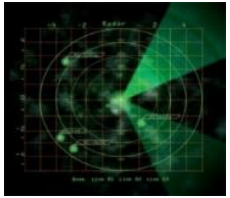
Left: Conventional B-mode ultrasound image
Right: SoS map (breast tumor - yellow)

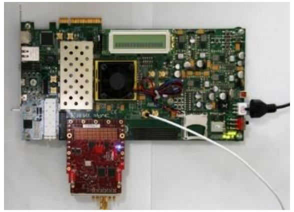


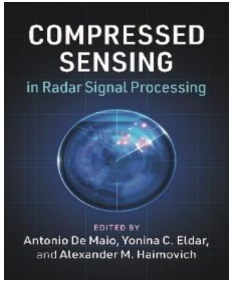
Radar/Time of Flight Imaging

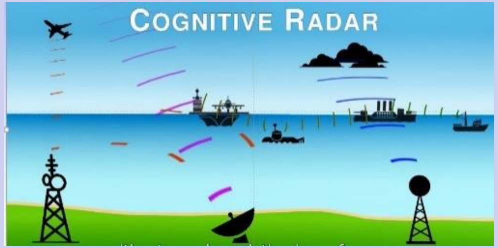
> Bar-Ilan and Eldar 14, Rossi et. al 14, Cohen and Eldar 18, Cohen et. al 18

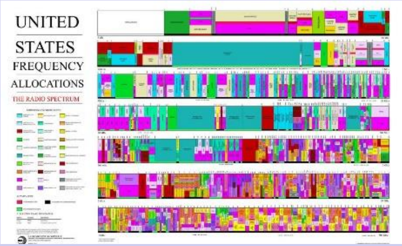
- Small, cheap radars with excellent resolution
- We can also reduce physical parameters:
  - Create a radar map in less time
  - Use fewer antenna elements
- Spectrum sharing between radar and communication over the same channel
- Free congested spectrum
- Fast frequency detection

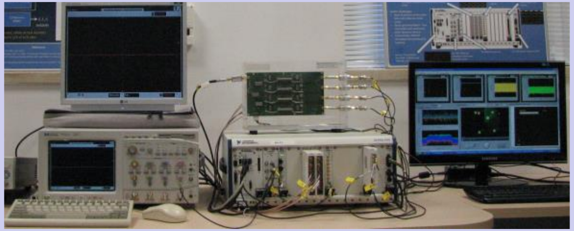




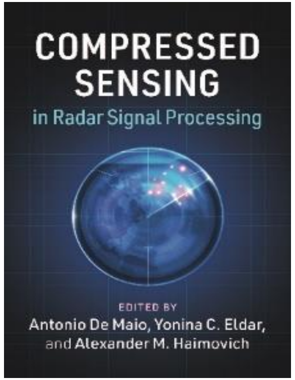








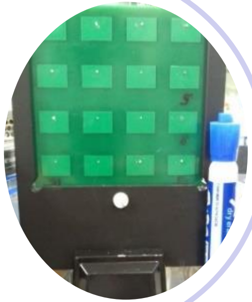
Sub-Nyquist and Cognitive Radar



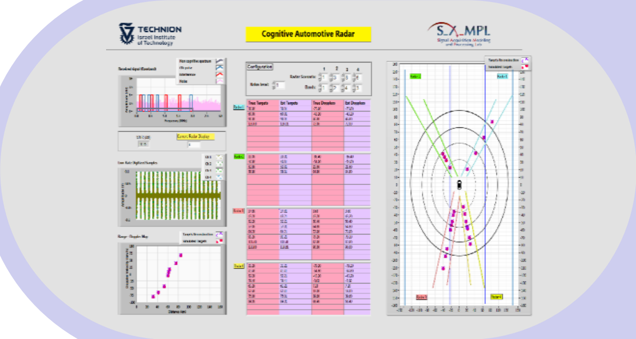
Cognitive Automotive Radar

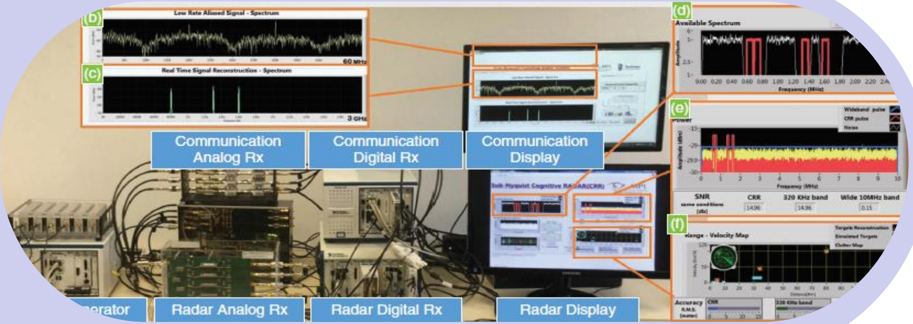
> Mulleti et. al 18-20

- Efficient radar systems that scan large environments
- Systems that can sense (radar) and communicate at the same time
- High resolution and high bit rate



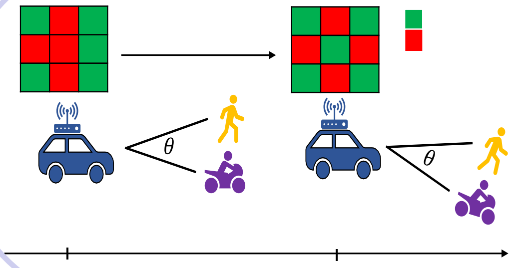
Joint radar/comm sub-Nyquist sampling with high resolution





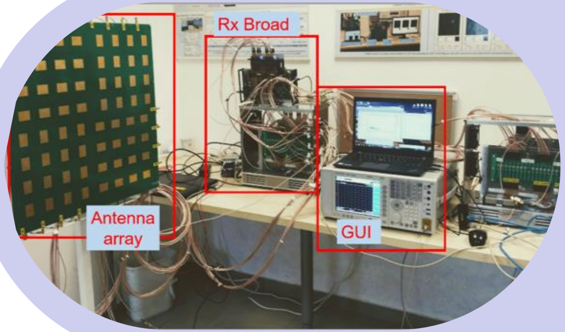
Deep-Sparse Antenna Array

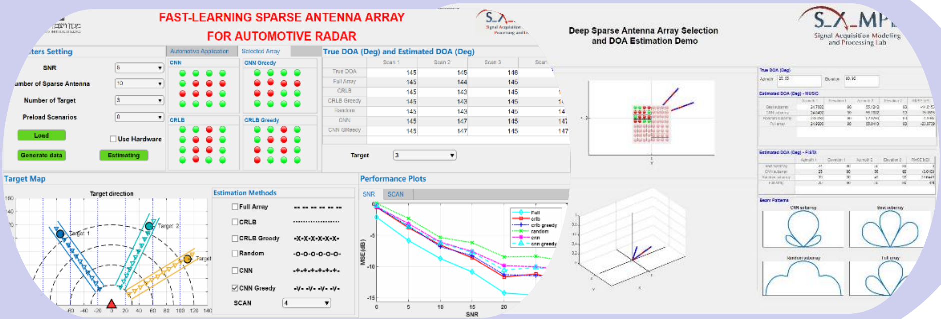
> Mulleti et. al 19-20



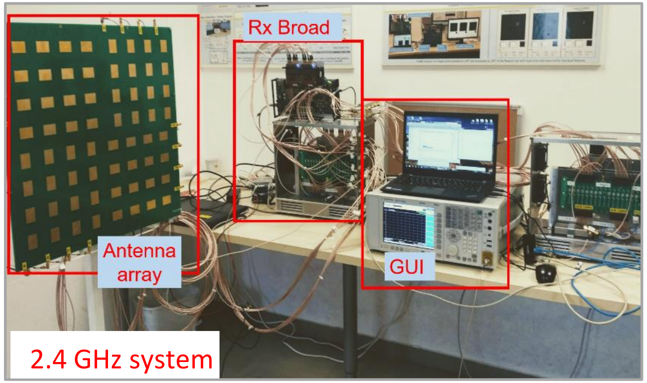
- High-res DOA ⇨ Large array ⇨ High-cost, power
- We propose NN-based sparse subarray selection
- The method is cognitive and adapts according to the current target scene
- The method is scalable and performs better than a non-adaptive random selection method

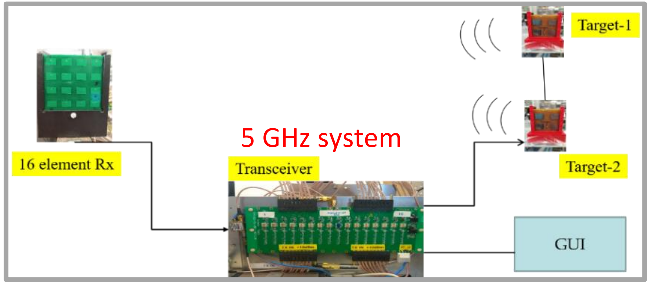
Sparse arrays are crucial in automotive radar to save battery!





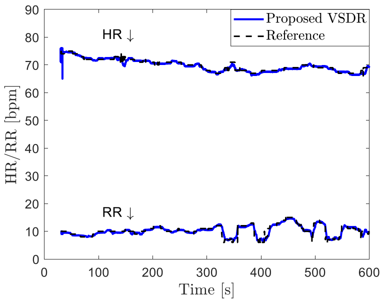
Deep-Sparse Antenna Selection

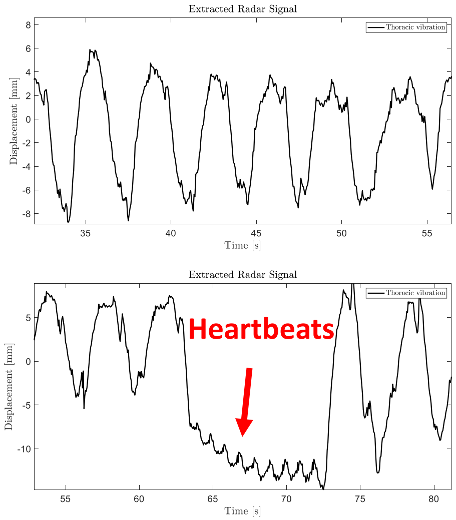


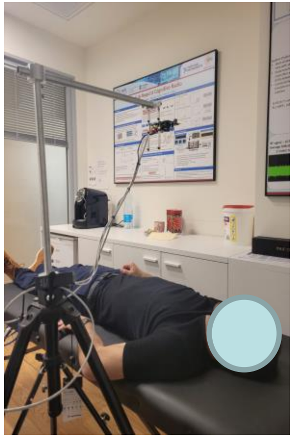


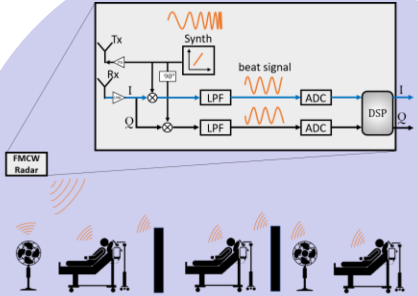
Remote Patient Monitoring Using mm-Wave Radar

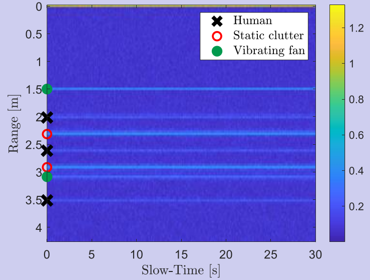
- Non-contact vital signs monitoring of multiple subjects
- Capable of analyzing very small movements
- Accurate human localization in a cluttered environment
- Interpretable mathematical modelling
- Utilizing the sparse nature of the signals

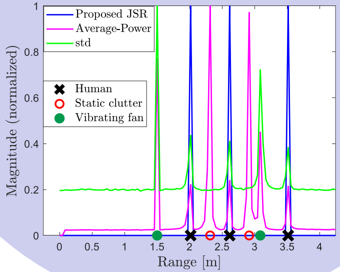








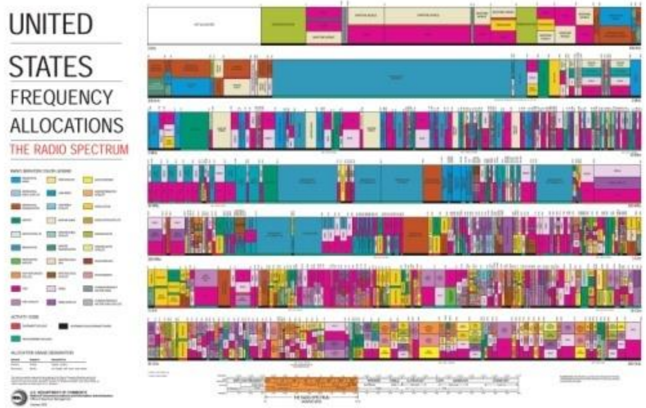


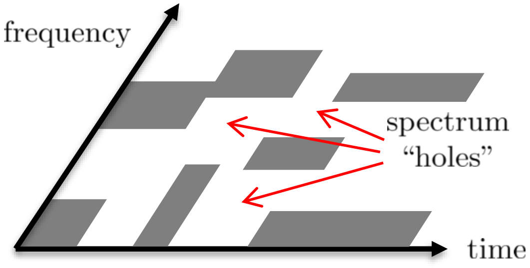


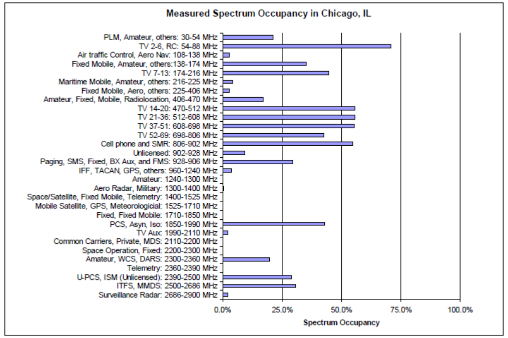
Cognitive Radio

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

Federal Communications Commission (FCC) frequency allocation



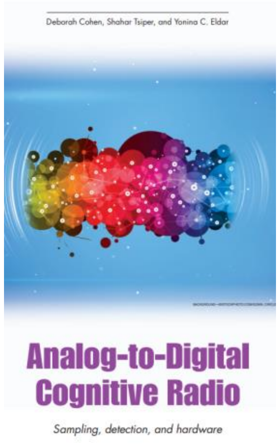




Shared Spectrum Company (SSC) – 16-18 Nov 2005

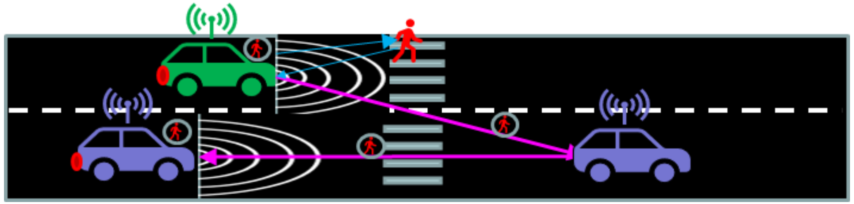
Licensed spectrum highly underused: E.g. TV white space, guard bands and more

Sub-Nyquist Cognitive Radio

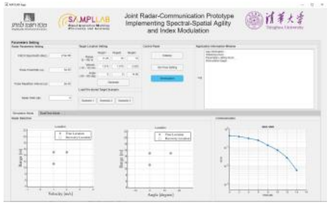


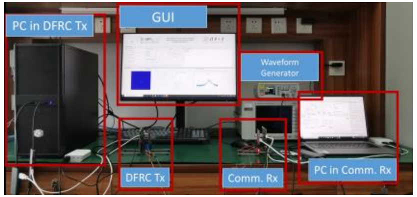
Dual Function Radar and Communication System

Collaboration with Prof. Yimin Liu group, Tsinghua University



Vehicle identifies nearby pedestrian and transmits the information to its surroundings using the FMCW radar signal





Hardware Demo

> Low cost mmWave radars are used for sensing vehicle surrounding

> The advantages of joint radar-communication system:

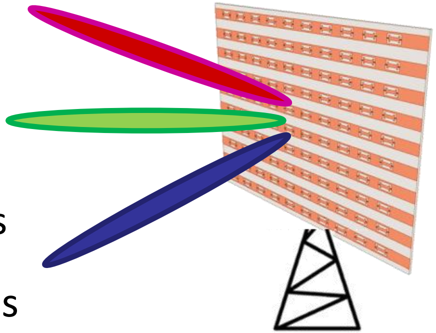
- Radars maintain their sensing function while communicating in parallel
- Additional safety measures!

Extending viewing angle using existing resources

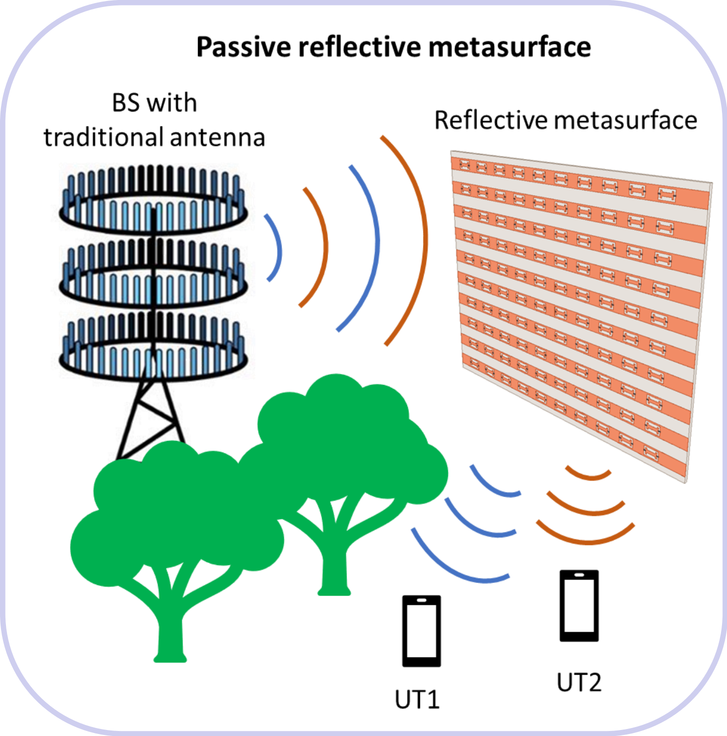
Dynamic Metasurface Antennas

> Shlezinger, Zhang, Alexandropoulos, and Eldar, et al, 2021

- 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)

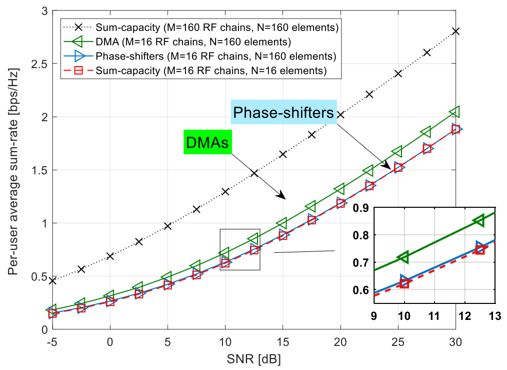


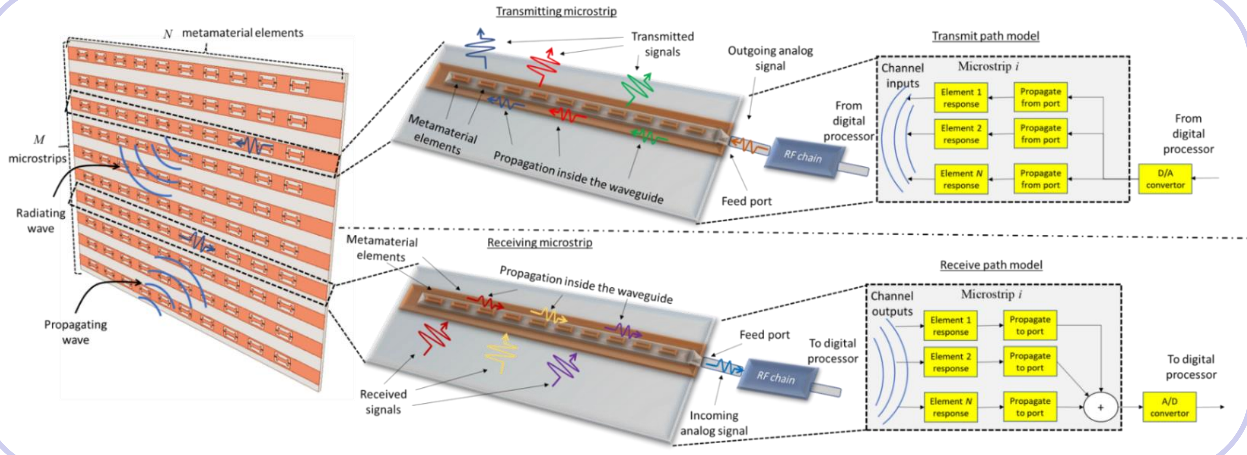
Metasurfaces for Analog Precoding: 1-bit Quantization

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

Precode data and reduce sampling and quantization rates!

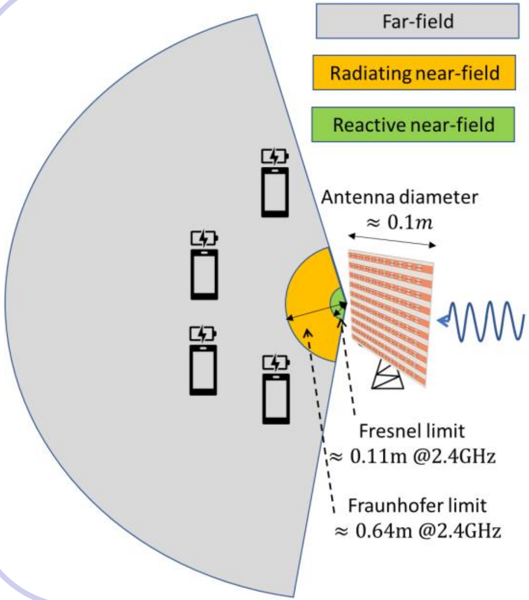
- Inherent tunable analog precoding in the antenna structure
- Low power, small hardware
- Enhanced frequency-selective analog processing
- Allows for 1-bit sampling with minimal loss of information

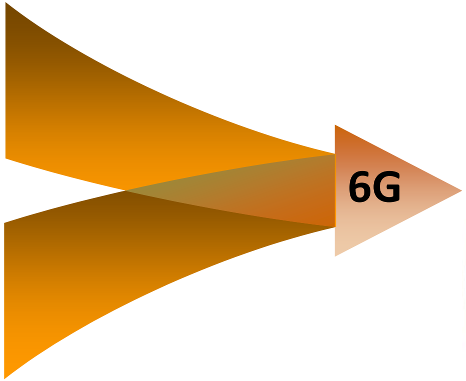




DMAs\RISs (Reconfigurable Intelligent Surfaces) for 6G Near-field Comm

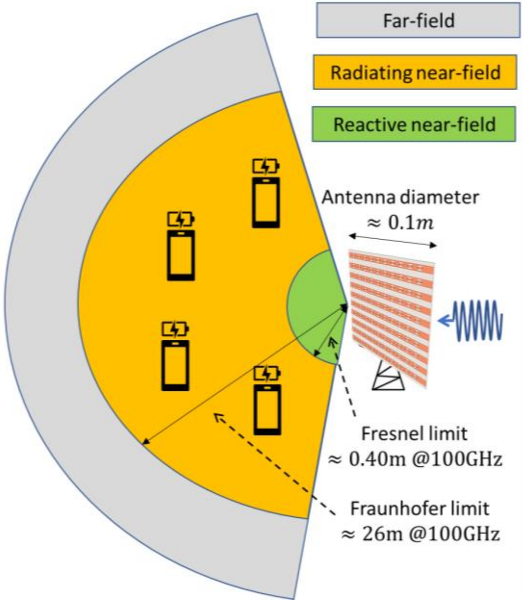
> Collaboration with George Alexandropoulos and Davide Dardari





Fresnel distance: $\sqrt[3]{\frac{D^4}{8\lambda}}$

Fraunhofer distance: $\frac{2D^2}{\lambda}$

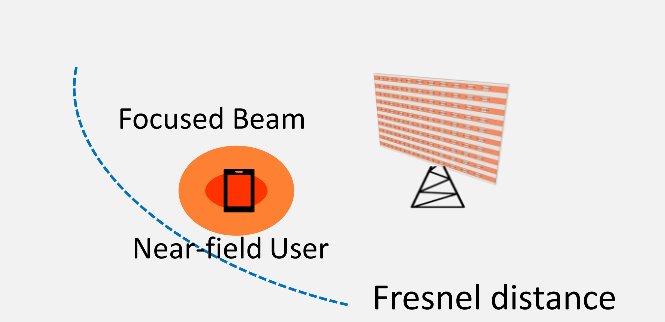


High-frequency bands & large antenna arrays leads to communication operating in the radiating near-field region!

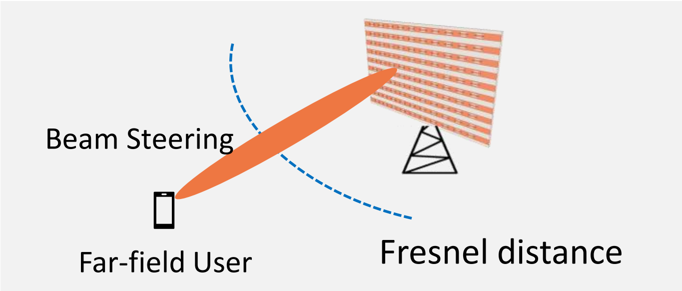
Zhang, Shlezinger and Eldar, et al, “6G Wireless Communications: From Far-field Beam Steering to Near-field Beam Focusing”, 2022

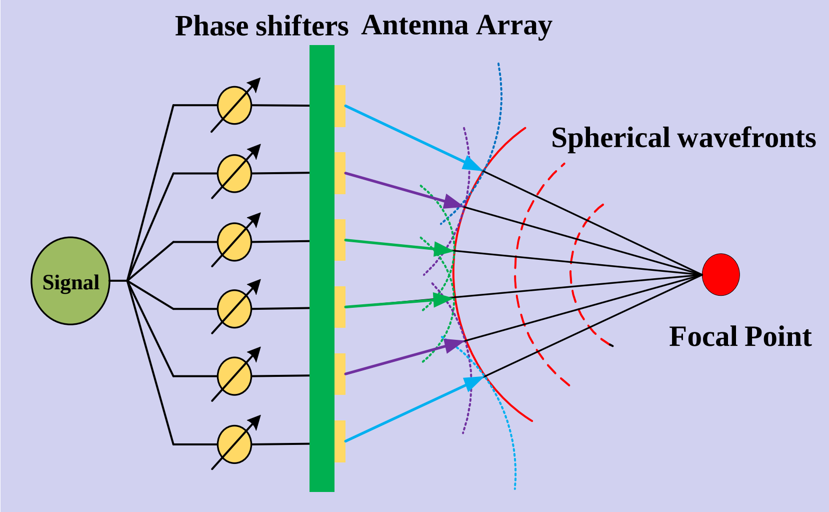
Near-field Beam Focusing: Spherical Wavefronts

- **Beam focusing (spherical waves)**: sends signals in a specific spatial location/depth along a direction



- **Beam steering (plane waves)**: sends signals towards a specific direction





Principle of using phased arrays to implement focused beam

- Compensate the transmission delay separately for each antenna, and add the signals at the focus point constructively (focusing)

Beam Focusing facilitates wireless communications

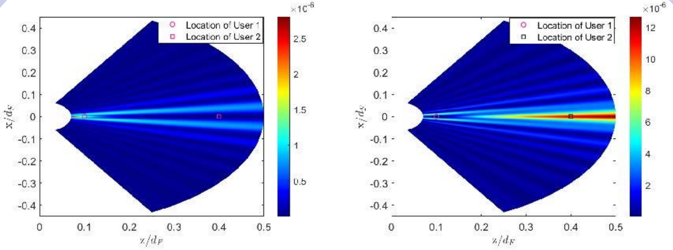
Near-field Wireless Communications: Applications

- Near-field multiple-user MIMO communications
  - Beam focusing can control multiuser interference in angle and distance domains!

Beam focusing provides a new DoF to mitigate interference!

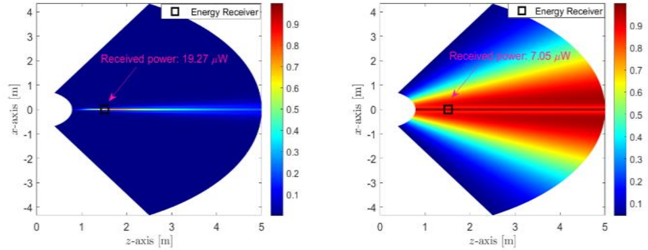
- Near-field wireless power transfer scenario
  - Beam focusing enables focusing the transmitter's energy on exact locations, resulting in more energy being received

Beam focusing enables high energy transfer efficiency!



(a) The normalized signal power of user 1 (b) The normalized signal power of user 2

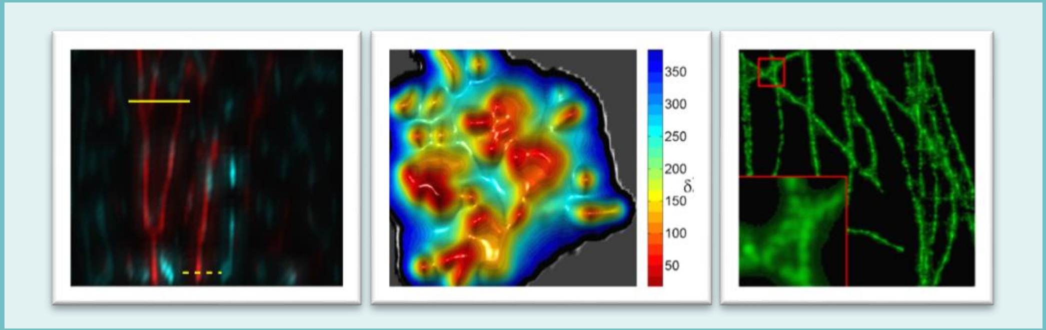
The normalized signal power of two users



(a) Single energy receiver located at the near-field region (b) Single energy receiver located at the far-field region

Normalized received power of the energy receiver

[1] Zhang, Shlezinger and Eldar, et al, "Near-field Wireless Power Transfer for 6G Internet-of-Everything Mobile Networks: Opportunities and Challenges", IEEE Communications Magazine, 2022
[2] Zhang, Shlezinger and Eldar, et al, "Beam Focusing for Near-Field Multi-User MIMO Communications", IEEE TWC, 2022
[3] Zhang, Shlezinger and Eldar, et al, "Beam Focusing for Multi-User MIMO Communications with Dynamic Metasurface Antennas", ICASSP, 2021



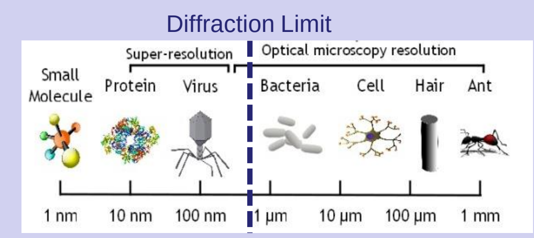
Super-Resolution in Microscopy and Ultrasound

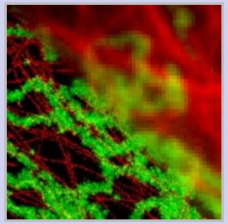
Signal Acquisition Modeling Processing and Learning

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

Photo: A. Mahmoud
Eric Betzig

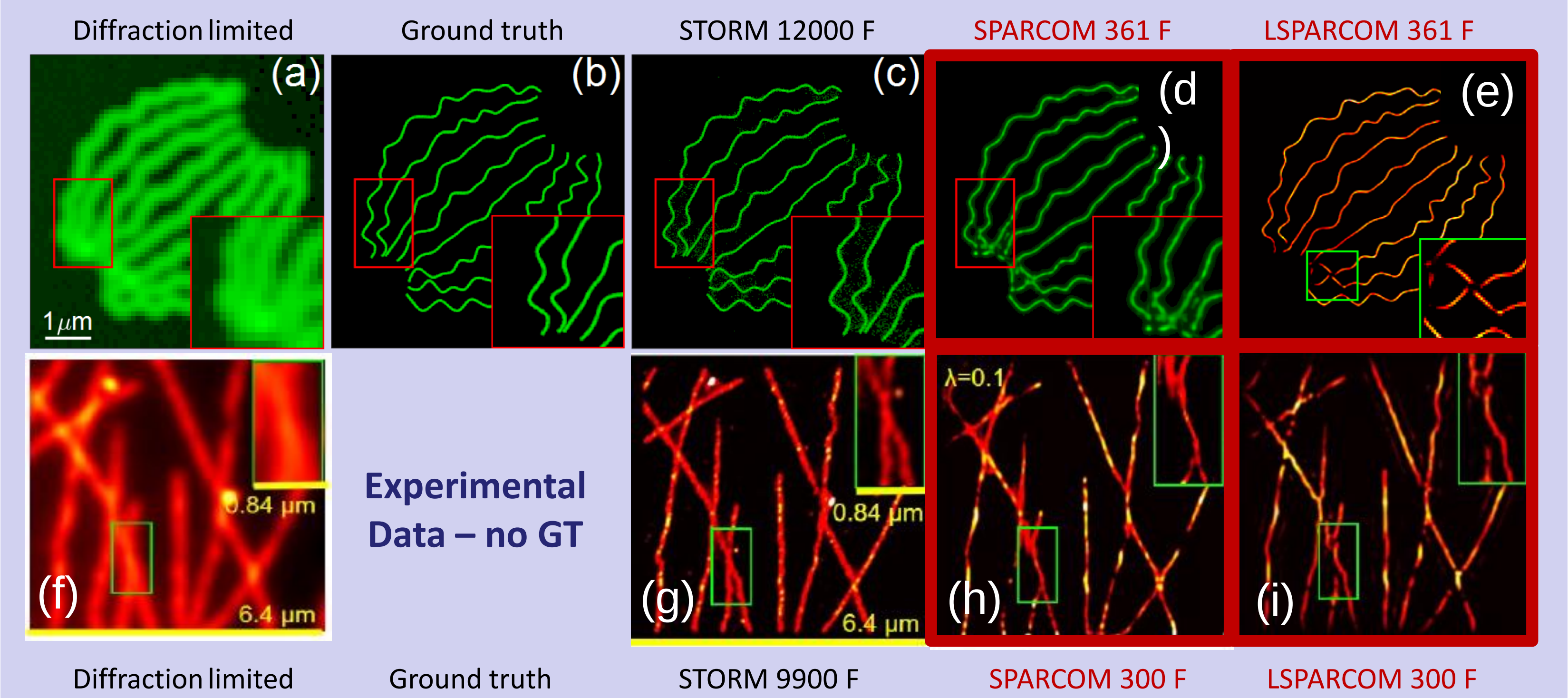
Photo: A. Mahmoud
Stefan W. Hell

Photo: A. Mahmoud
William E. Moerner

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

SPARCOM: Super Resolution Correlation Microscopy

> Solomon et. al 18; Dardikman-Yoffe and Eldar, 20
> Collaboration with the group of Prof. Moti Segev



Data from: http://bigwww.epfl.ch/smlm/

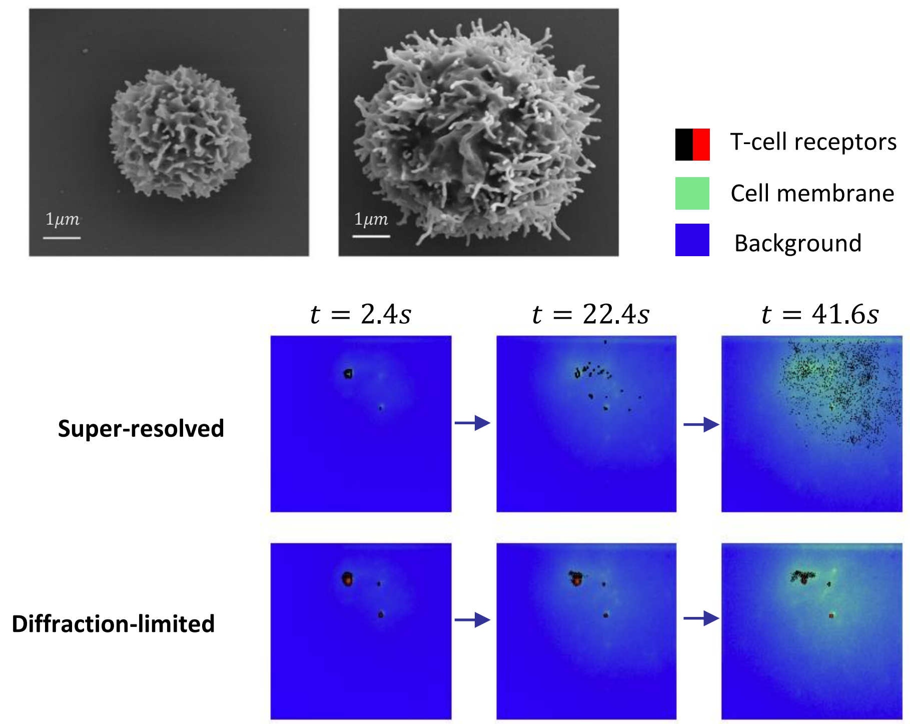
Improved resolution over STORM – two orders of magnitude faster

Super-resolution of T-cell Receptors

> Collaboration with the group of Prof. Haran from Weizmann

- Immune response of T-cells involves change in T-cell receptor (TCR) molecules' locations w.r.t cell membrane
- Dynamic scene (gradually changes every few seconds)
- SPARCOM was used separately for each step (x100 shorter compared to STORM)

Paving the way to live cell inspection of TCR arrangement



AutoSPARCOM: Single-Image Super Resolution Microscopy

- Learned SPARCOM is trained on **simulations:** what if the input doesn't fit our simulations?
- AutoSPARCOM trained on patches from the input itself **– no training data is needed!**
- Currently tested both on simulations and experimental data (T cells, GIST-T1/882*)

*Collaboration with the group of Prof. Avi Schroeder

DEEP LEARNING IN BIOLOGICAL IMAGE AND SIGNAL PROCESSING

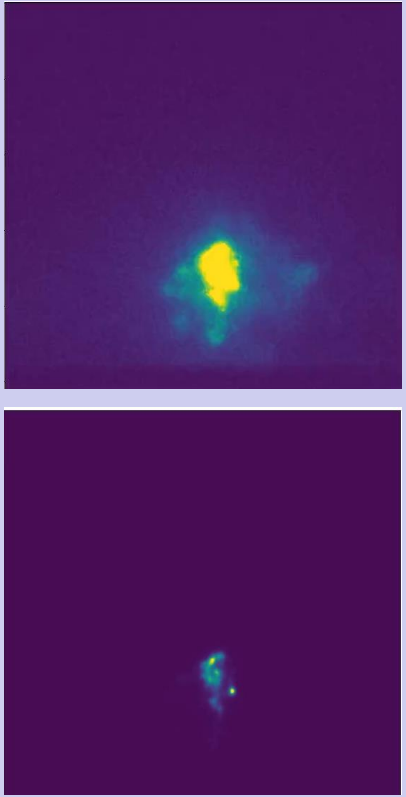
Yair Ben Sahel, John P. Bryan, Brian Cleary, Samouil L. Farhi, and Yonina C. Eldar

Deep Unrolled Recovery in Sparse Biological Imaging

Achieving fast, accurate results

Original Frames

SR Images



T-cell receptors

Background

Super Resolution Ultrasound

Super-resolution techniques surpass the classical limit of diffraction for imaging and allow the detection and separation of subwavelength features

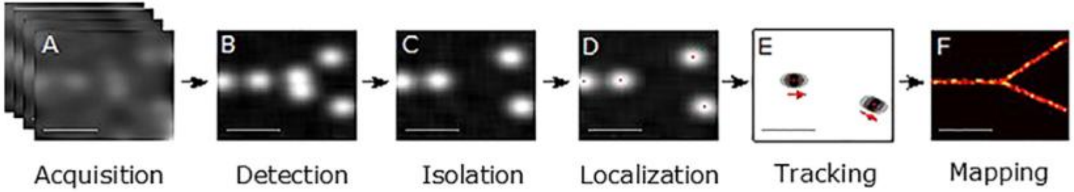
Super-resolution vascular imaging – how is it actually done?

01 Intravascular administration of an Ultrasound Contrast Agent containing microbubbles

02 Scanning with an ultrasound scanner

03 Localization with micrometric precision of each microbubble

04 The accumulation of localizations yields a super-resolved map of the microvasculature



Christensen-Jeffries et al.

Super Resolution Ultrasound for Breast Lesion Characterization

- Breast cancer is the most common malignancy in women
- Detection is usually done using mammography or MRI, with ultrasound serving as an adjunct tool for diagnosis
- Malignant breast tumors depend on neoangiogenesis for their growth and spread

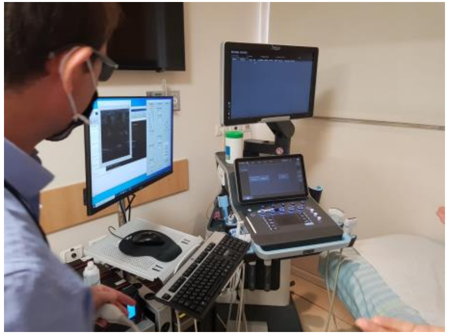
Learned super resolution ultrasound for improved breast lesion characterization

Or Bar-Shira[1], Ahuva Grubstein[2,3], Yael Rapson[2,3], Dror Suhami[2,3], Eli Atar inst2, Keren Peri-Hanania[1], Ronnie Rosen[1], and Yonina C. Eldar[1]

SAMPLLAB
Signal Acquisition Modeling Processing and Learning

RABIN MEDICAL CENTER
BEILINSON • HASHARON

Can we use super-resolution vascular ultrasound imaging to demonstrate neoangiogenesis?



21 female patients with breast lesions – both benign and malignant

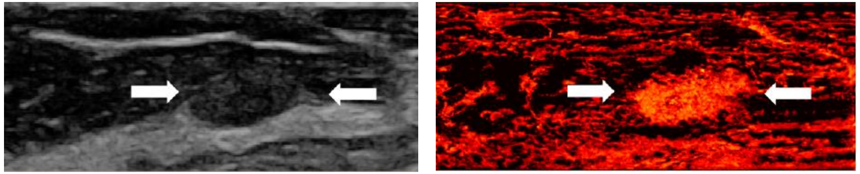
Ultrasound scanning after IV administration of Contrast Material (Sonovue)

Advanced deep learning methods were applied to the data to get super-resolved images

Super-Resolved Vascular Reconstructions

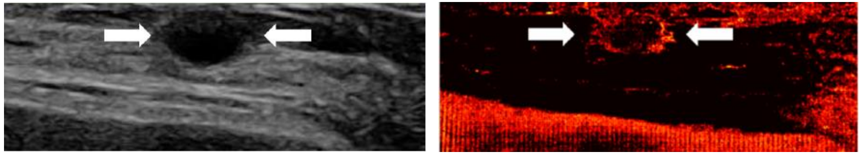
All together, we can see that the 3 recoveries exhibit different vascular patterns, corresponding with the different histologic types:

B-Mode ultrasound	Super-resolution recovery	



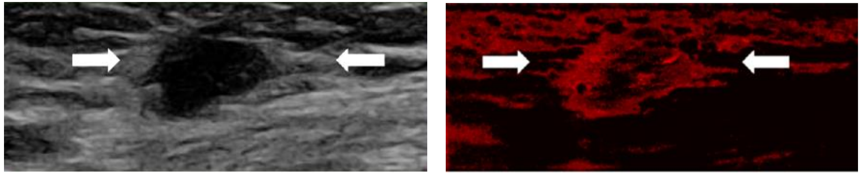
The super resolution recovery shows an oval, well circumscribed mass with homogeneous high vascularization

Fig 1 – Fibroadenoma



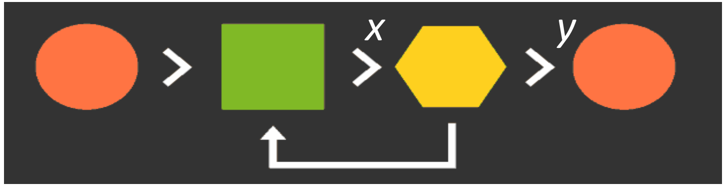
The super resolution recovery shows a round structure with high concentration of blood vessels at the lesion periphery

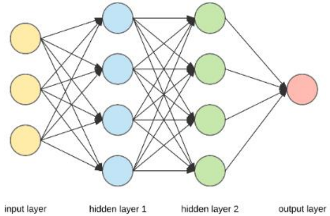
Fig 2 – Cyst



The super resolution recovery shows an irregular mass with ill-defined margins, high concentration of blood vessels at the periphery of the mass, and a low concentration of blood vessels at the center of the mass

Fig 3 – Invasive Ductal Carcinoma



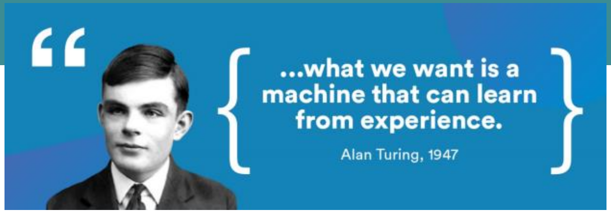


Model-Based Artificial Intelligence

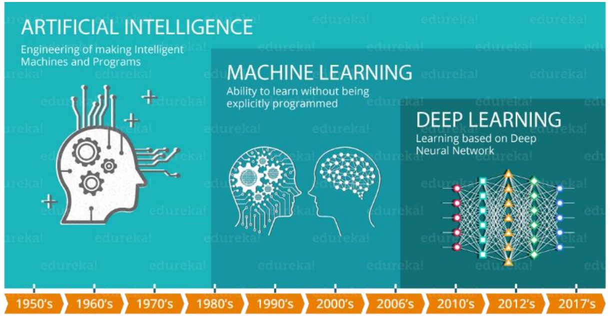
WEIZMANN INSTITUTE OF SCIENCE

SAMPLLAB
Signal Acquisition Modeling Processing and Learning

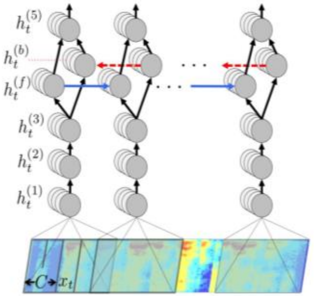
The Deep Learning Revolution



- Deep neural networks (DNNs) achieve superior performance in multiple areas:
  - Computer vision
  - Speech processing
  - Problems that are difficult to tackle using conventional optimization **methods**



Speech to text:



Self driving cars:

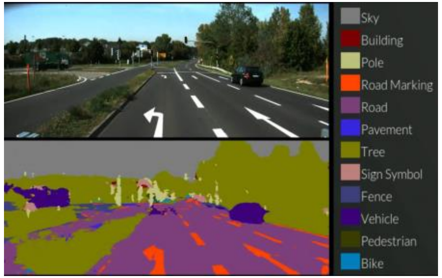
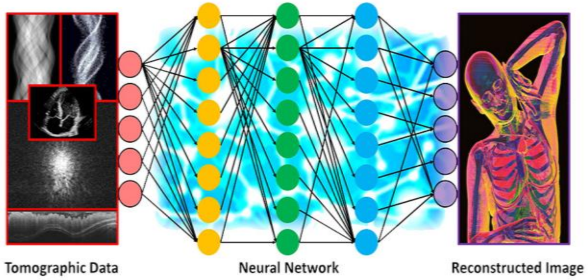


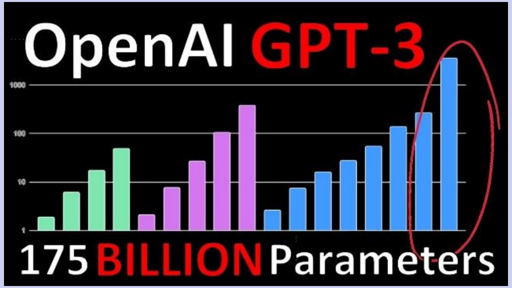
Image recovery:

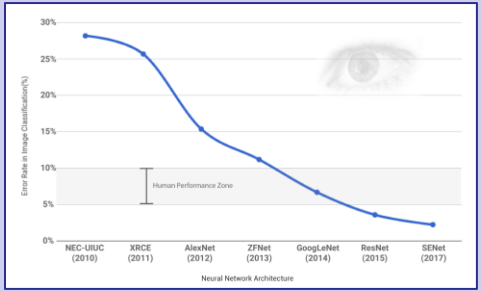


Challenges

- > Unprecedent empirical success!
- > But….
  - Large training sets
  - Computationally exhaustive training
  - Interpretability?
  - Robustness?
  - Generalization?
  - Complexity…

AI spawned faces



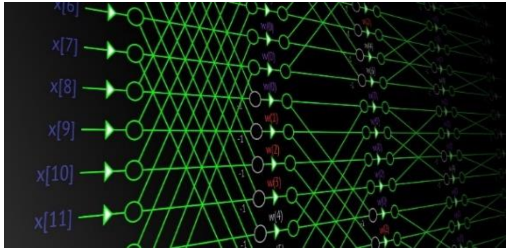


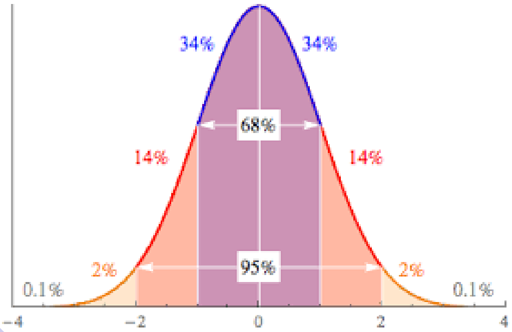
Model Based Signal Processing

- 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

$f(g(x), y)$

(e.g. $\|y - g(x)\|$)

Output x

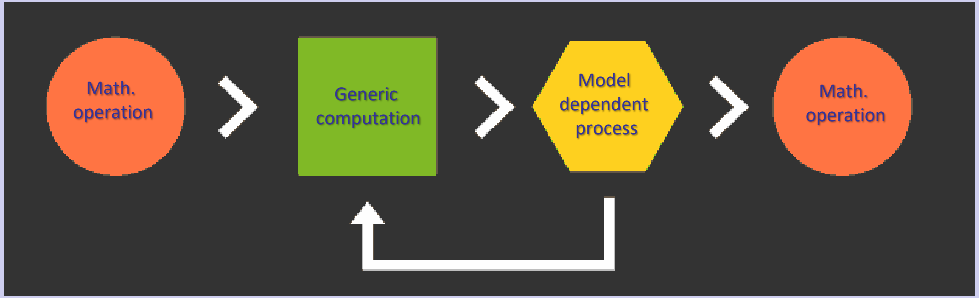
$y \approx g(x)$

Model-Based vs. Deep Learning

> Model-based signal processing:

Input y

(Measurement)

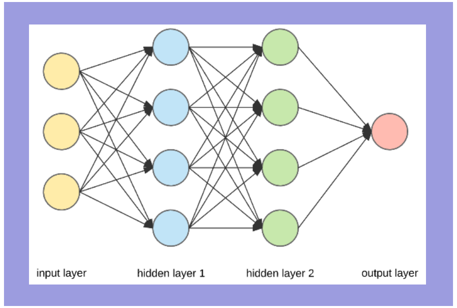


Output x

> Deep learning:

Many Inputs

New y

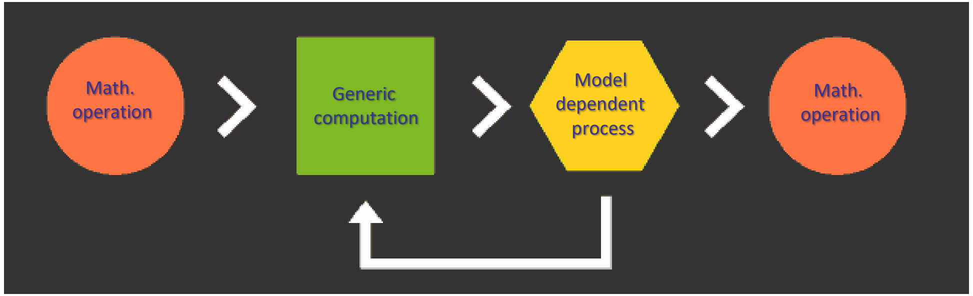


Many Outputs

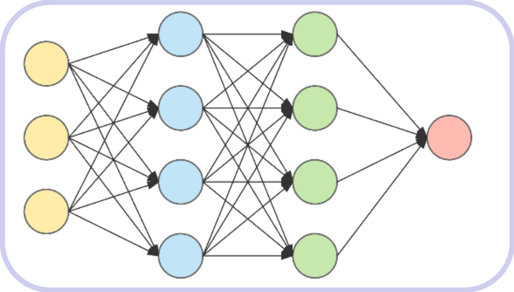
x

Model-Based Deep Learning

- Model-based signal processing:



- Deep learning:



- How to combine?

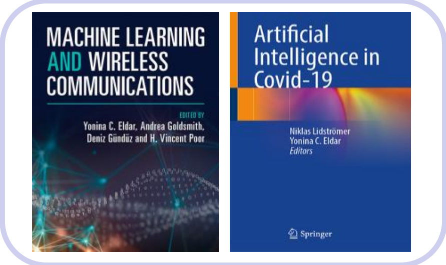
1. Integrate model-based algorithms into deep networks

Deep unfolding / unrolling

2. Integrate deep networks into model-based algorithms

Data-driven hybrid algorithms

N. Shlezinger, Y. C. Eldar, and S. P. Boyd, "Model-Based Deep Learning: On the Intersection of Deep Learning and Optimization"

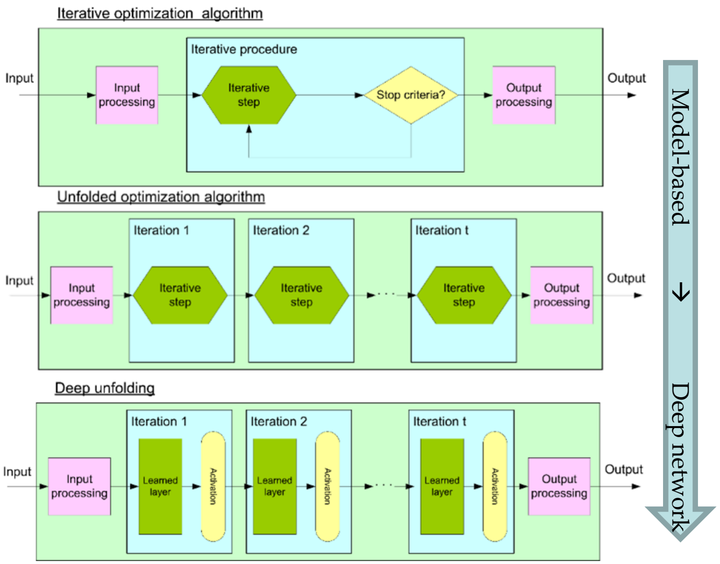


Deep Unfolding

> 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

Recent review in SP Magazine

Vishal Monga, Yuelong Li, and Yonina C. Eldar

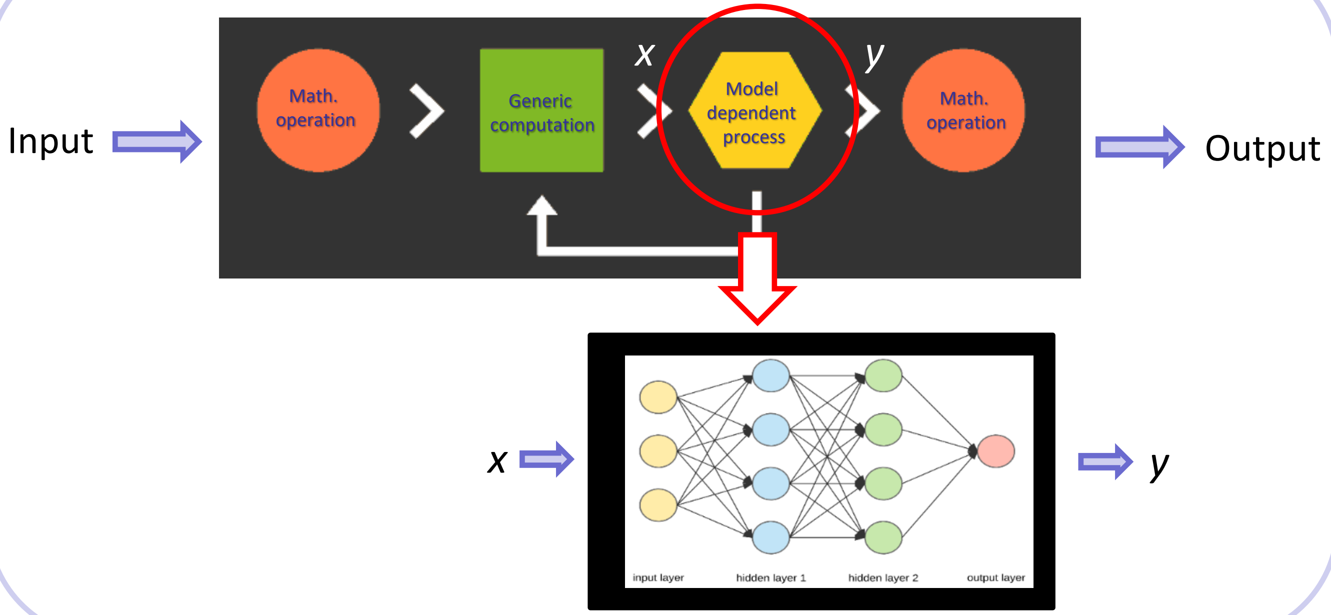
Algorithm Unrolling

Interpretable, efficient deep learning for signal and image processing

Data Driven Hybrid Algorithms

Advantages:

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

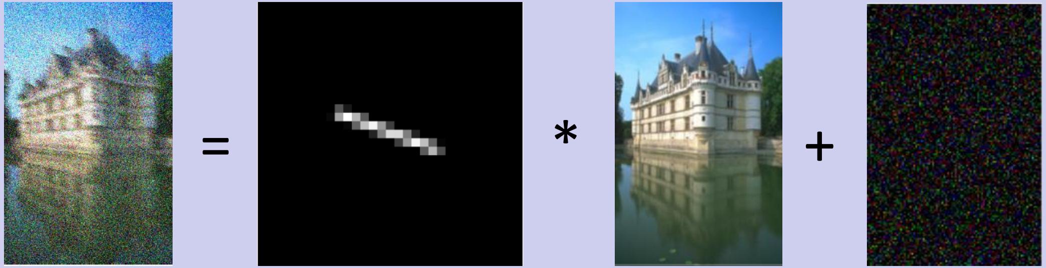


Recent Reviews:

N. Farsad, N. Shlezinger, A. J. Goldsmith, and Y. C. Eldar, "Data-Driven Symbol Detection via Model-Based Machine Learning"
N. Shlezinger, Y. C. Eldar, and S. P. Boyd, "Model-Based Deep Learning: On the Intersection of Deep Learning and Optimization"

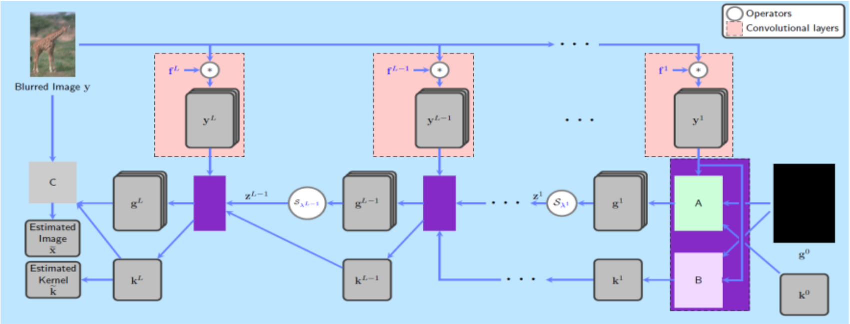
DUBLID: Deep Unrolling for Blind Deblurring

> Li, Tofighi, Monga and Eldar, 19



y Blurred Image = k Blur Kernel * x Sharp Image + n Random Noise

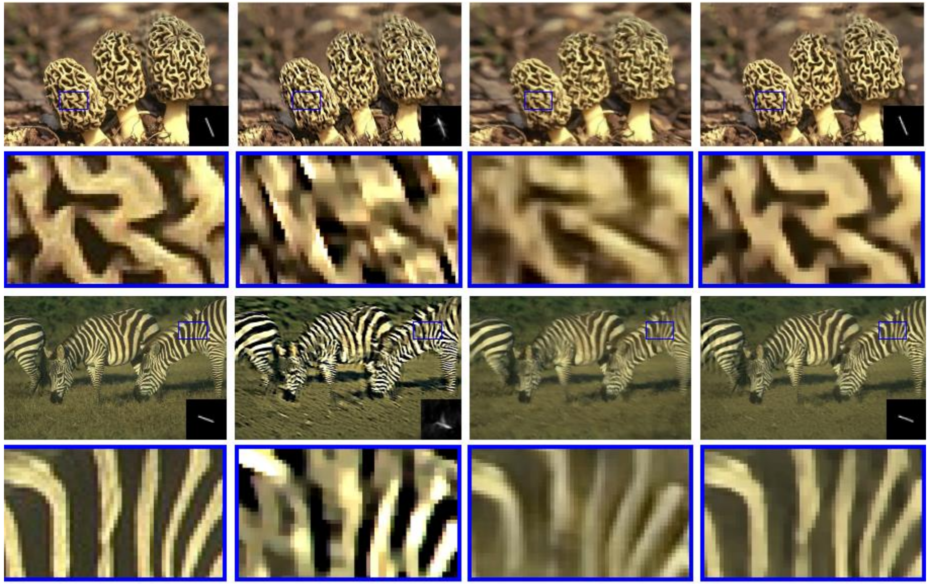
- Many deblurring methods based on optimization (e.g. total variation)
- We perform total variation in the gradient domain ∇**y≈k***∇**x**
- We solve the problem by a variable splitting approach and then unfold



Deblurring Results

- Training based on BSDS500 dataset
- Rapid inference

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



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

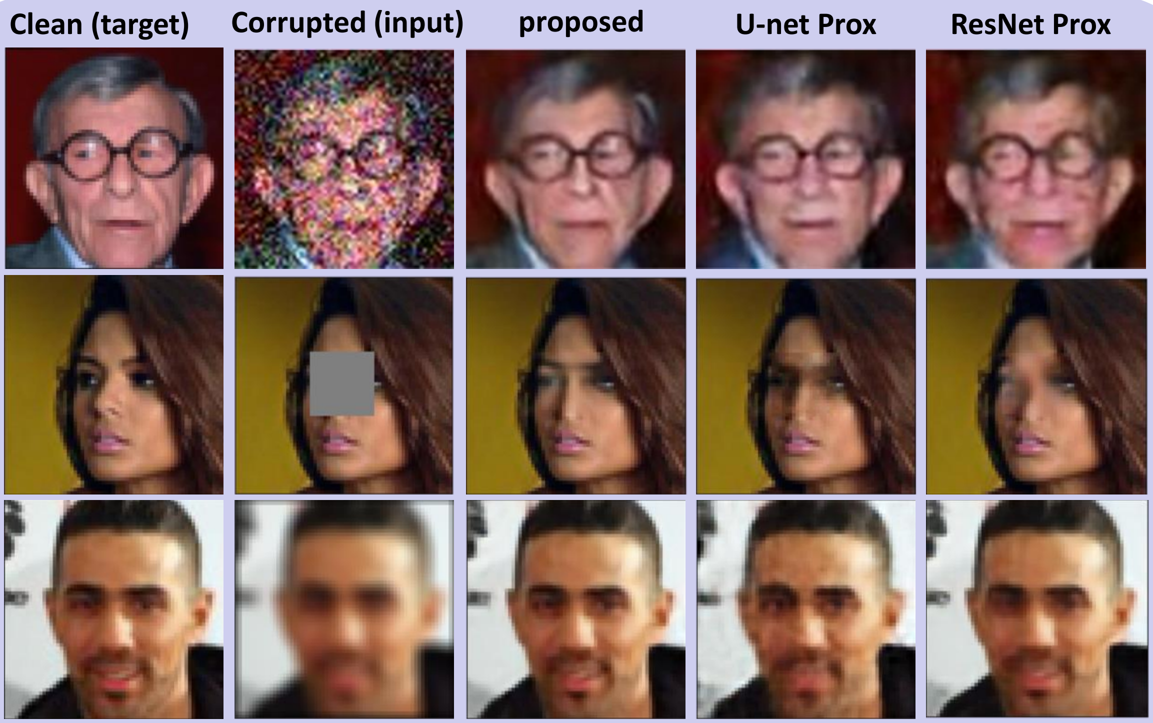
QUANTITATIVE COMPARISON OVER AN AVERAGE OF 200 IMAGES AND 4 KERNELS. THE BEST SCORES ARE IN BOLD FONTS

Metrics	DUBLID	Perrone *et al.* [24]	Tao *et al.* [31]	Nah *et al.* [37]	Xu *et al.* [33]	Kupyn *et al.* [77]
PSNR (dB)	**27.30**	22.23	25.32	24.82	24.02	23.98
ISNR (dB)	**4.45**	2.06	2.42	1.92	1.12	1.05
SSIM	**0.88**	0.76	0.83	0.80	0.78	0.78

Unfolded FlowNet Results

> Wei, Van Gorp, Carabarin, Freedman, Eldar, and van Sloun, 21

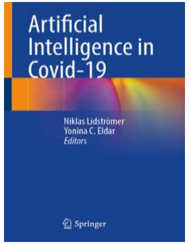
- Comparison with other neural proximal mappings (ResNet and U-net)
- FlowNet outperforms both on the CelebA dataset



Eindhoven University

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



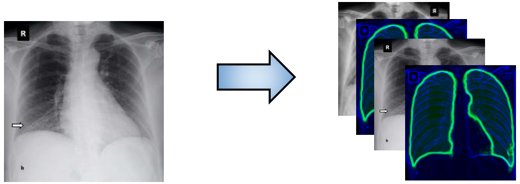
European Radiology
https://doi.org/10.1007/s00330-021-08050-1

IMAGING INFORMATICS AND ARTIFICIAL INTELLIGENCE

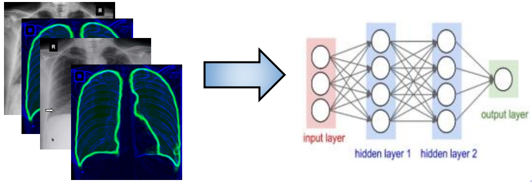
COVID-19 classification of X-ray images using deep neural networks

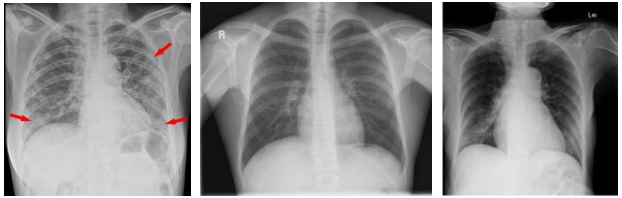
Daphna Keidar[1] · Daniel Yaron[2] · Elisha Goldstein[3] · Yair Shachar[4] · Ayelet Blass[2] · Leonid Charbinsky[5] · Israel Aharony[5] · Liza Lifshitz[5] · Dimitri Lumelsky[5] · Ziv Neeman[5] · Matti Mizrachi[6,7] · Majd Hajouj[6,7] · Nethanel Eizenbach[6,7] · Eyal Sela[6,7] · Chedva S. Weiss[8] · Philip Levin[8] · Ofer Benjaminov[8] · Gil N. Bachar[9,10] · Shlomit Tamir[9,10] · Yael Rapson[9,10] · Dror Suhami[9,10] · Eli Atar[9,10] · Amiel A. Dror[6,7] · Naama R. Bogot[8] · Ahuva Grubstein[9,10] · Nogah Shabshin[5] · Yishai M. Elyada[11] · Yonina C. Eldar[2]

Step 1: Pre-processing + Segmentation

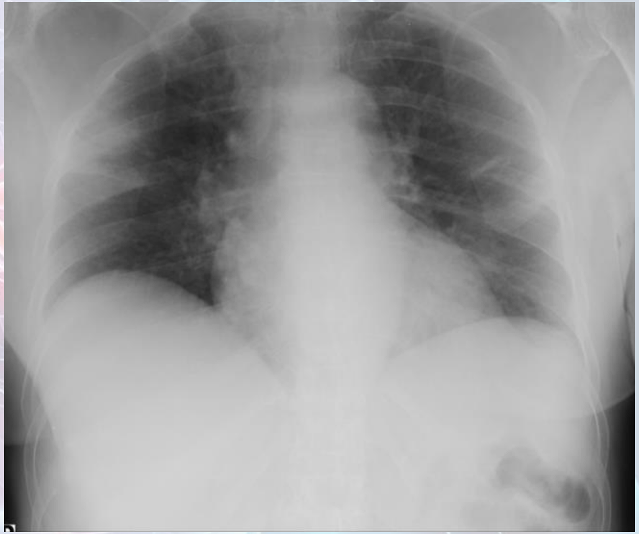


Step 2: Deep learning algorithm

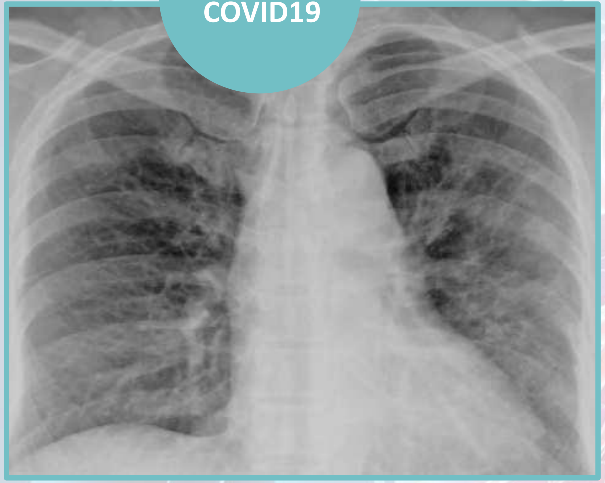




Data

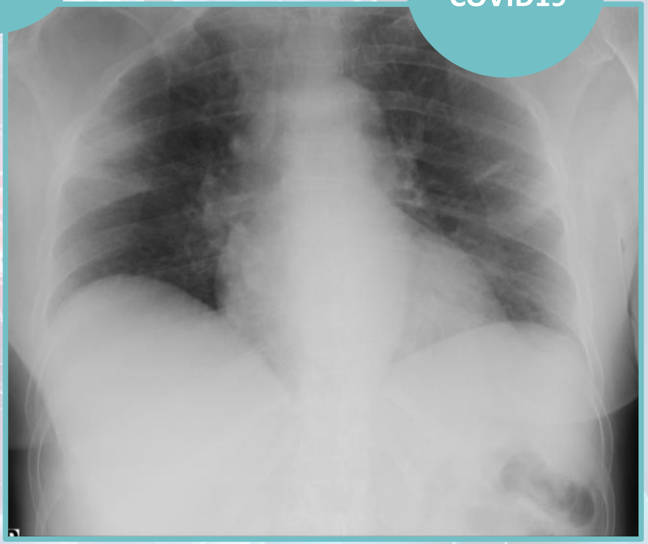


Data



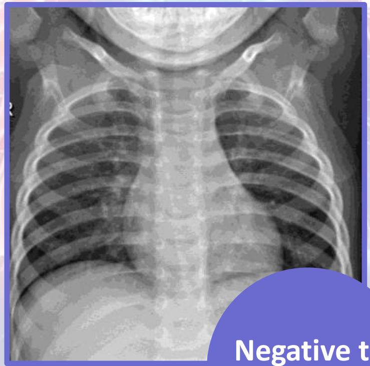
Positive to COVID19

Positive to COVID19



Positive to COVID19

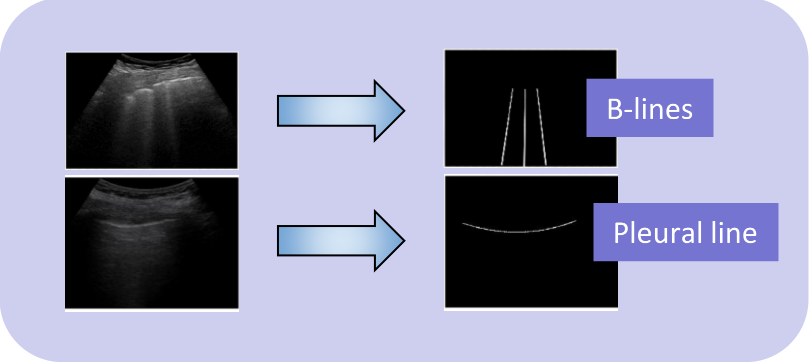
Negative to COVID19

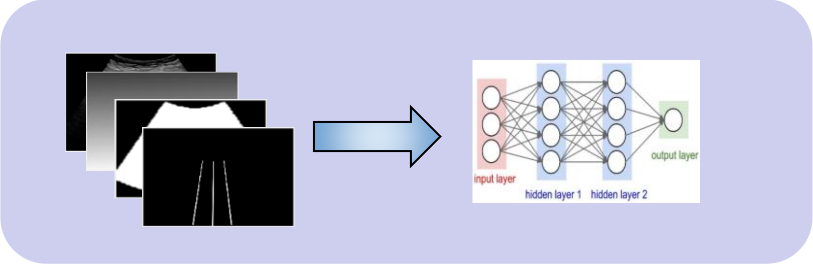


Negative to COVID19

COVID19 US Task Force

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

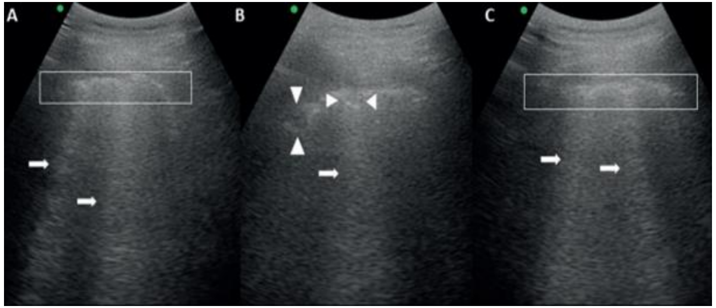




IEEE TRANSACTIONS ON MEDICAL IMAGING, PREPRINT – UNDER REVIEW

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

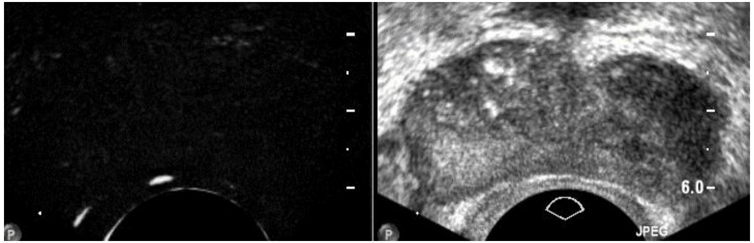


Removing Tissue Background via Deep Learning

> Solomon et. al. 2018

CORONA: Convolutional rObust pRincipal cOmpoNent Analysis

- 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

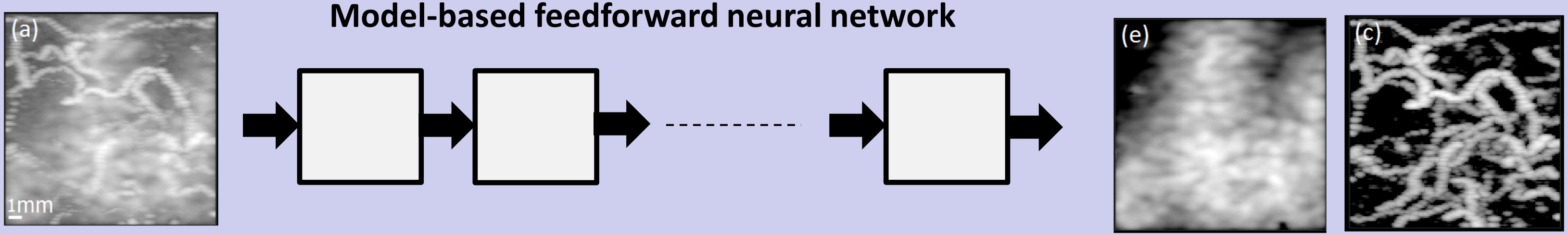
Van Sloun, Cohen, Eldar

INVITED PAPER

Deep Learning in Ultrasound Imaging

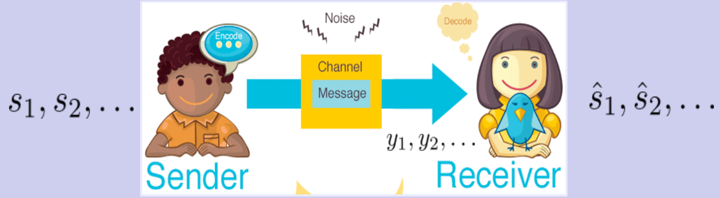
This article provides an overview of use of deep, data-driven learning strategies in ultrasound systems, from the front-end to advanced applications. The authors discuss the use of these new computational approaches in all aspects of ultrasound imaging, ranging from ideas that are at the interface of 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.

Model-based feedforward neural network



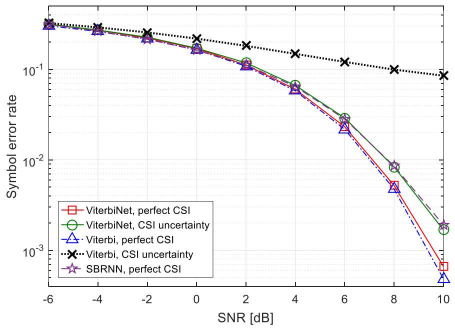
Viterbinet: Symbol Detection with Unknown Channels

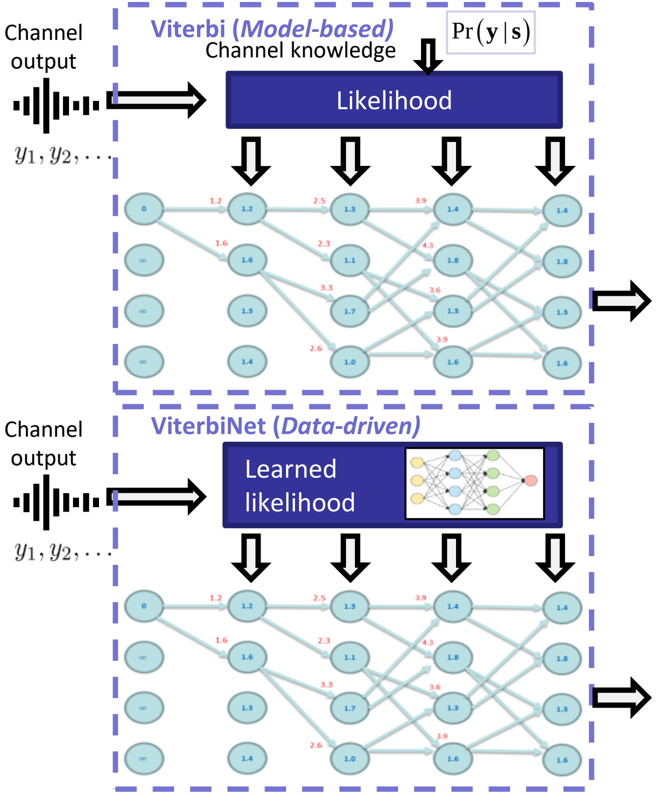
> Shlezinger, Farsad, Eldar and Goldsmith 19



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

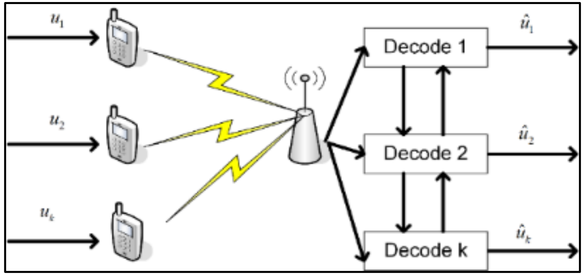
Optimal symbol detection from minimal training

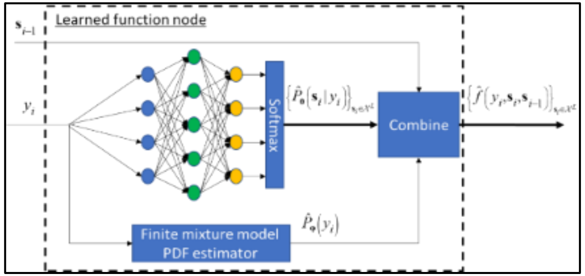


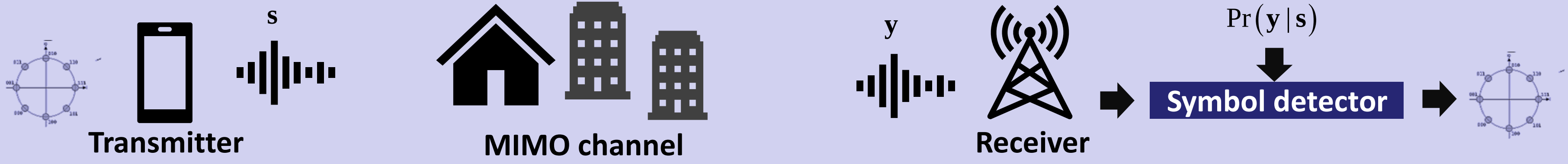


Deep Symbol Detection

- Symbol detection over challenging wireless channels
- Performance almost the same as knowing the channel
- Training done within existing header
- Supports multiuser settings, fast fading, IoT and more







Generalization Guarantees for LISTA and Learned-ADMM

> Shultzman, Azar, Eldar and Rodrigues 22

- Analysis of generalization error (GE) for learned ISTA or ADMM with l layers, $\boldsymbol{a}^{(l)}$:

$$GE = \sup_{\boldsymbol{a}^{(l)}} |L_D(\boldsymbol{a}^{(l)}) - L_S(\boldsymbol{a}^{(l)})|$$

L_D, L_S are the expected and empirical losses

- Bound the GE using **Rademacher complexity**

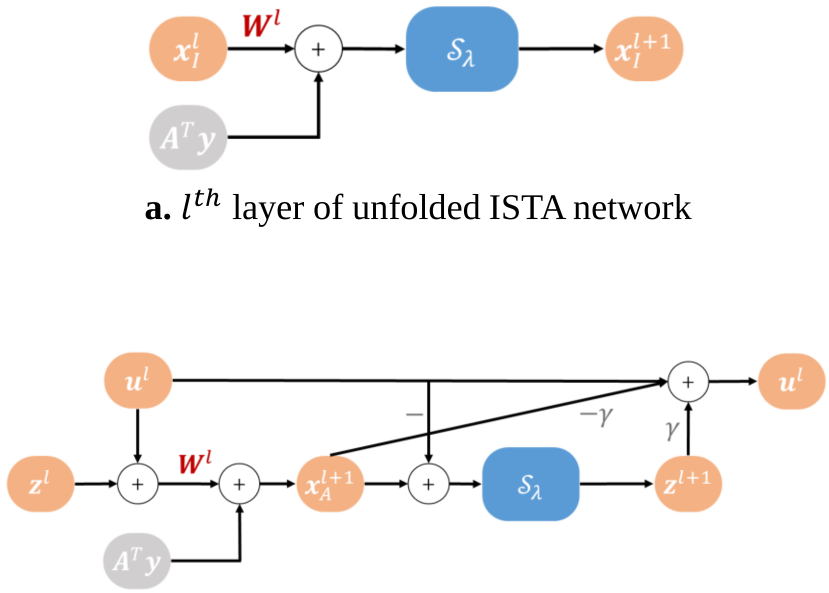
Theorem

GE of a LISTA network with soft-threshold λ, l layers, tested on m samples from training set S, weights norm bounded by B, and a 1-Lipscithz loss function, satisfies

$$\mathbb{E}_S[GE] \leq 2\max\left\{\frac{B^l}{\sqrt{m}} - \lambda\frac{B^l - 1}{B - 1}, 0\right\}$$

- The GE of ReLU networks is bounded by an exponential $\mathbb{E}_S[GE] \leq 2B^l/\sqrt{m}$
- Gives a design rule for networks with non-increasing GE (as a function of the number of layers)

$$B \leq 1 + \lambda/\sqrt{m}$$



a. l^{th} layer of unfolded ISTA network

b. l^{th} layer of unfolded ADMM network

Optimization Guarantees for LISTA and Learned-ADMM

> Pu, Eldar and Rodrigues 22

- Analysis of training loss for learned ISTA and ADMM for sparse recovery $\mathbf{y} = \mathbf{A}\mathbf{x} + \mathbf{n}$
- Given P training pairs $\{x_i, y_i\}$ and using gradient descent with an MSE loss
- We derive a bound on P in order for the training loss to converge to 0
- LADMM requires less training data than LISTA - LADMM converges faster!

Theorem

The training loss converges to zero if the number of training samples satisfies

$$P \leq \left(\frac{c}{c_H}\right)^2$$

The constant c_H depends on the dimensions and number of layers. In addition, c_H of LADMM is larger than c_H of LISTA.

Efficient, Interpretable, High Resolution Technology: Results and Vision

Couple physics and algorithms to learn more from less data

Exploit end-to-end structure in model based and data driven methods

Mathematical and Physical 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 ...

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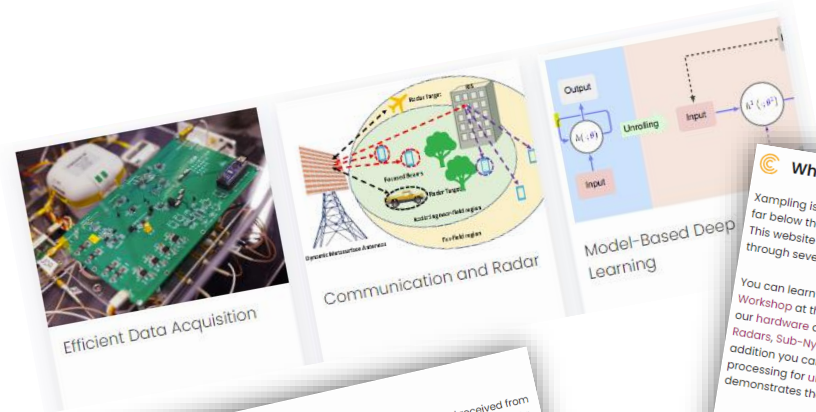
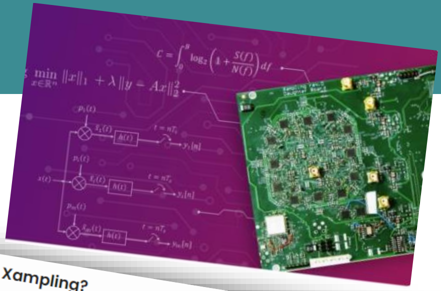
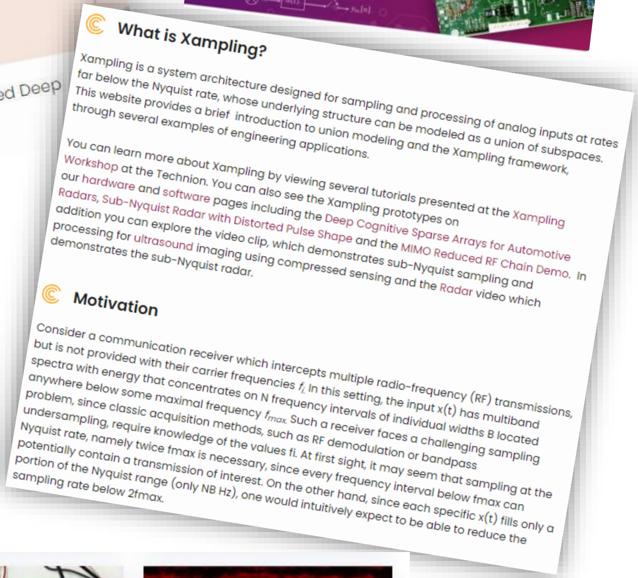






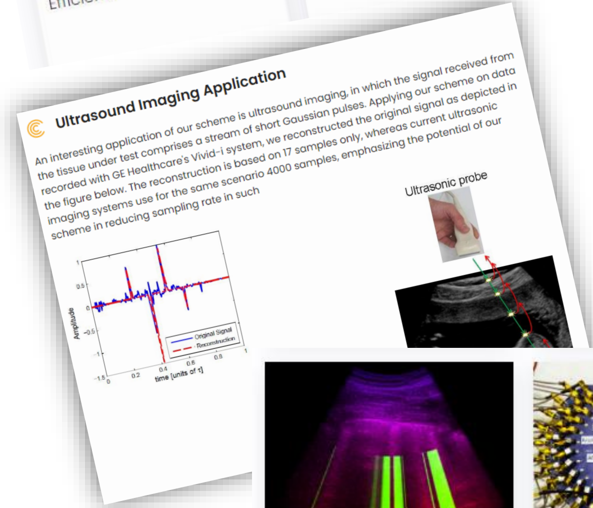
What is Xampling?

Xampling is a system architecture designed for sampling and processing of analog inputs at rates far below the Nyquist rate, whose underlying structure can be modeled as a union of subspaces. This website provides a brief introduction to union modeling and the Xampling framework, through several examples of engineering applications.

You can learn more about Xampling by viewing several tutorials presented at the Xampling Workshop at the Technion. You can also see the Xampling prototypes on our hardware and software pages including the Deep Cognitive Sparse Arrays for Automotive Radars, Sub-Nyquist Radar with Distorted Pulse Shape and the MIMO Reduced RF Chain Demo. In addition you can explore the video clip, which demonstrates sub-Nyquist sampling and processing for ultrasound imaging using compressed sensing and the Radar video which demonstrates the sub-Nyquist radar.

Motivation

Consider a communication receiver which intercepts multiple radio-frequency (RF) transmissions, but is not provided with their carrier frequencies f_i. In this setting, the input x(t) has multiband spectra with energy that concentrates on N frequency intervals of individual widths B located anywhere below some maximal frequency f_{max}. Such a receiver faces a challenging sampling problem, since classic acquisition methods, such as RF demodulation or bandpass undersampling, require knowledge of the values fi. At first sight, it may seem that sampling at the Nyquist rate, namely twice fmax is necessary, since every frequency interval below fmax can potentially contain a transmission of interest. On the other hand, since each specific x(t) fills only a portion of the Nyquist range (only NB Hz), one would intuitively expect to be able to reduce the sampling rate below 2fmax.



Ultrasound Imaging Application

An interesting application of our scheme is ultrasound imaging, in which the signal received from the tissue under test comprises a stream of short Gaussian pulses. Applying our scheme on data recorded with GE Healthcare's Vivid-i system, we reconstructed the original signal as depicted in the figure below. The reconstruction is based on 17 samples only, whereas current ultrasonic imaging systems use for the same scenario 4000 samples, emphasizing the potential of our scheme in reducing sampling rate in such

https://www.weizmann.ac.il/math/yonina/

SAMPL Team

SAMPLLAB
Signal Acquisition Modeling
Processing and Learning

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

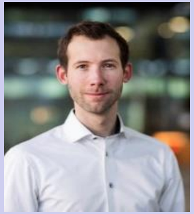
Collaborators (Partial…)


Miguel Rodrigues


Andrea Goldsmith


Muriel Medard


Fan Liu


Ruud Van Sloun


Davide Dardari

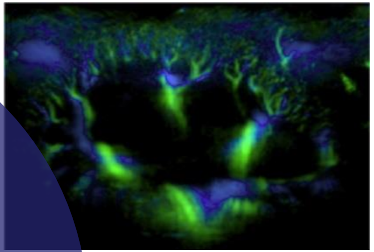

Vishal Monga

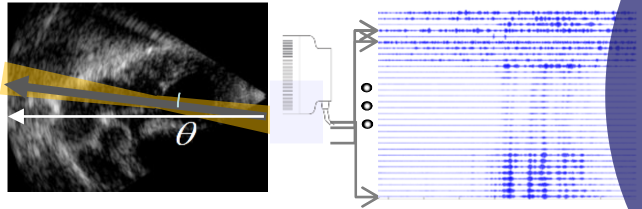

Nir Shlezinger

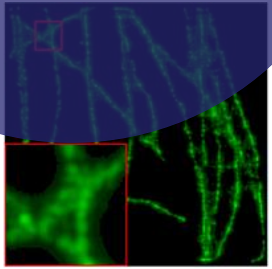

Tianyao Huang


George Alexandropoulos

Thank You!







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Looking for graduate students and post-docs!