Fast Analog-to-Digital Compression for High Resolution Imaging

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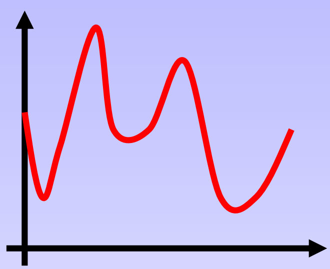
Sampling: "Analog Girl in a Digital World…"

Judy Gorman 99

Analog world



$x(t)$

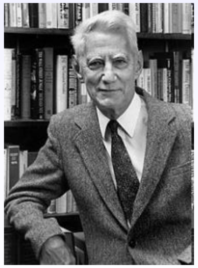
- Radar
- Image
- Ultrasound…

Sampling
Analog-to-Digital
(ADC)

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

H. Nyquist

C. Shannon



Digital world

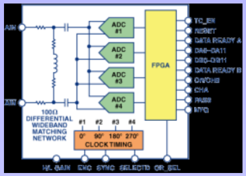
$c[n]$

- Signal processing
- Image denoising
- Analysis…

Processing

Limitations of Nyquist-Rate Sampling

- Large bandwidth requires high rate samplers
  - High rate communications
  - High resolution e.g. in radar and imaging
- High sampling rates lead to:
  - Large and expensive hardware-intensive systems
  - High-energy systems
  - Large digital databases that are difficult to process, store and transmit
- In medical imaging high rates often translate into long scanning times or high radiation dosages







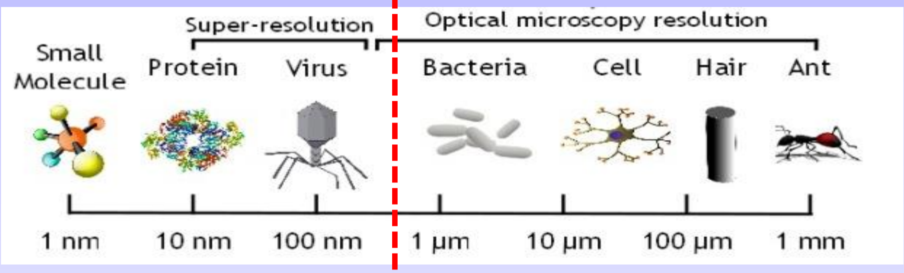
ADCs, the front end of all digital devices, remain a major bottleneck

Q.: Can we recover information if we sample at a sub-Nyquist rate?

Super Resolution

- All measuring devices are bandwidth or resolution limited
- Abbe's diffraction limit in optical imaging: $DL = \frac{\lambda}{2NA}$
  Spatial resolution is proportional to half the imaging wavelength

Diffraction Limit

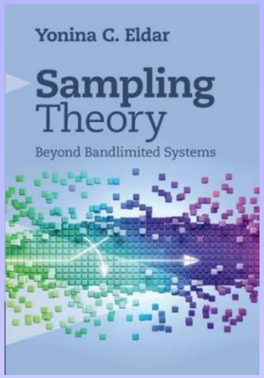


- Spatial resolution in an antenna array or ultrasound probe is proportional to the aperture

Can we algorithmically recover the lost information using principles of sampling theory?

Xampling: Sub-Nyquist Sampling

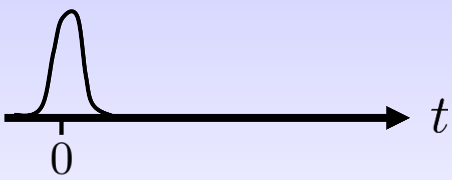
Xampling = Compression + Sampling

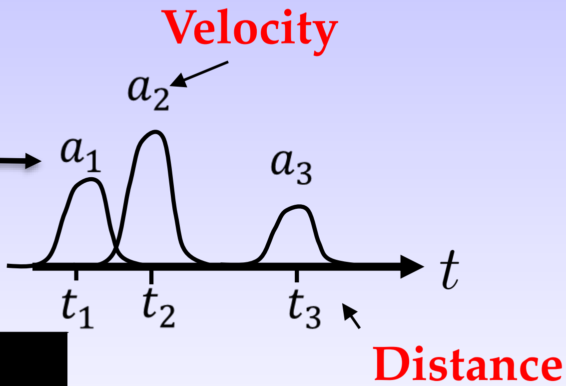


- Reduce sampling rate in each ADC
- Reduce the number of elements used for imaging

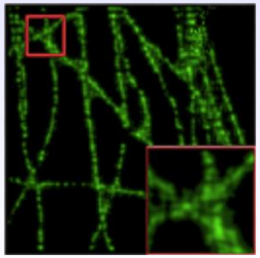
Main idea:

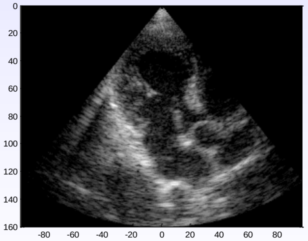
- Exploit structure





- Exploit processing task

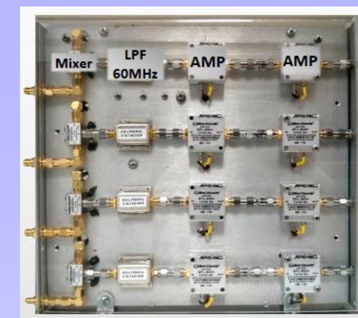


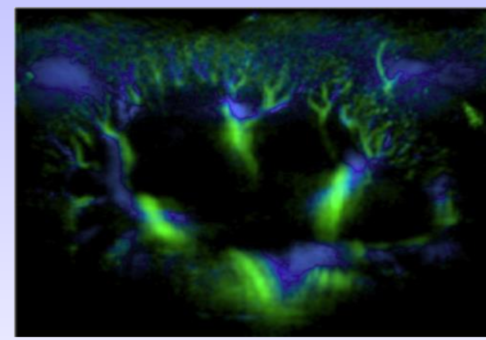


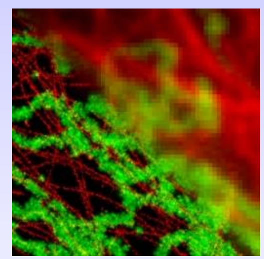
Substantial rate reduction and super resolution is possible!

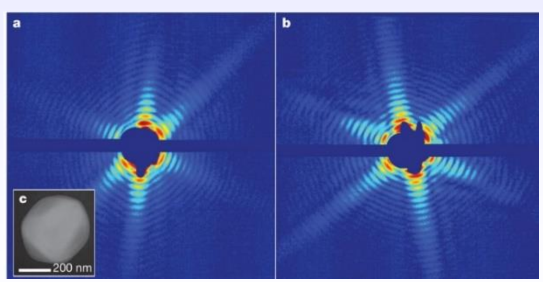
Talk Outline

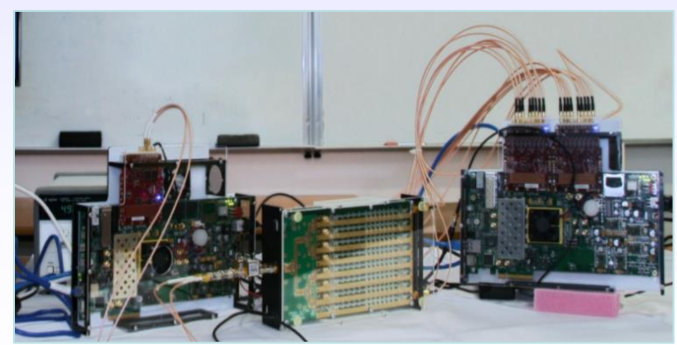
- Motivation for structure
- Xampling: Compression + sampling of analog signals
- Application to communication, radar and ultrasound
- Spatial subsampling
- Super resolution in microscopy and ultrasound
- Phase retrieval





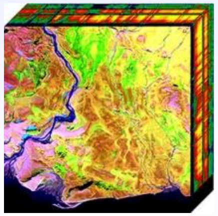


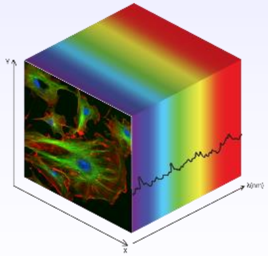




Part 1:

Motivation



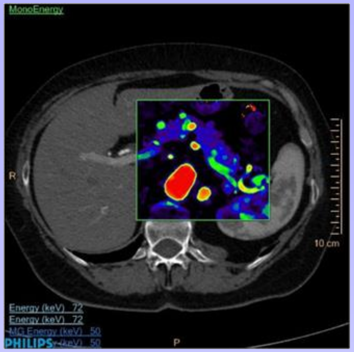


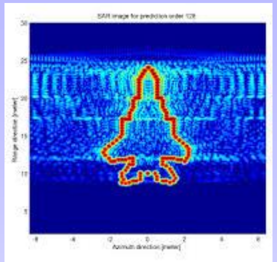
Imaging Modalities

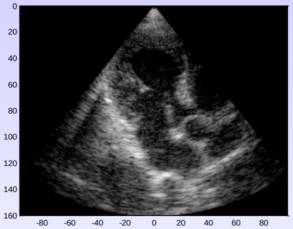
- Imaging in different frequency bands:

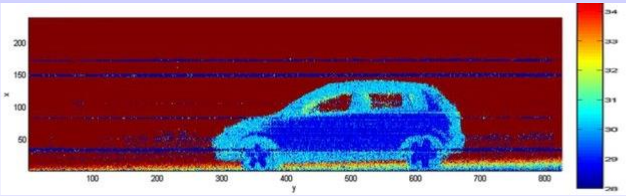
  Spectral CT, hyperspectral imaging

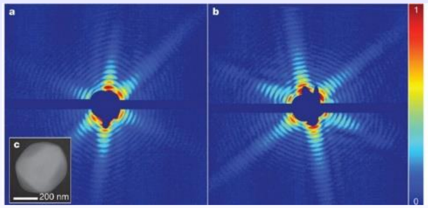
- Radar and ultrasound imaging:
  - Multiple antennas
  - Streams of pulses
  - Beamforming
- Optical imaging: Lack of phase information





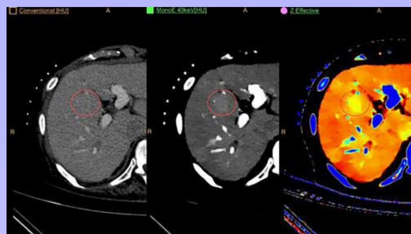
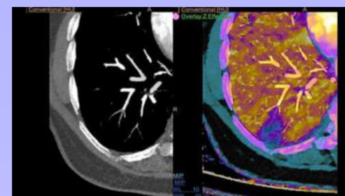
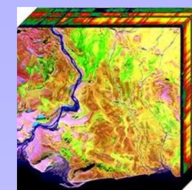
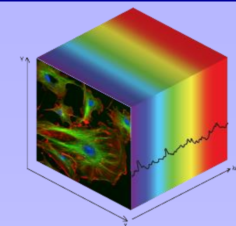




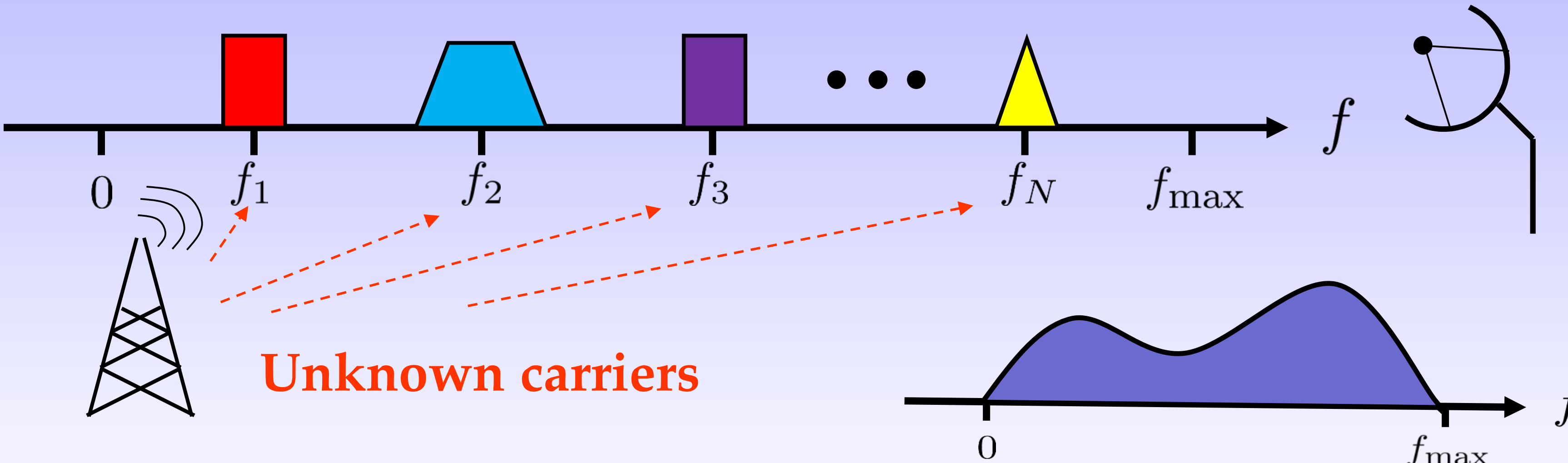


General framework for rate reduction and super resolution image recovery

Multiple Frequency Bands

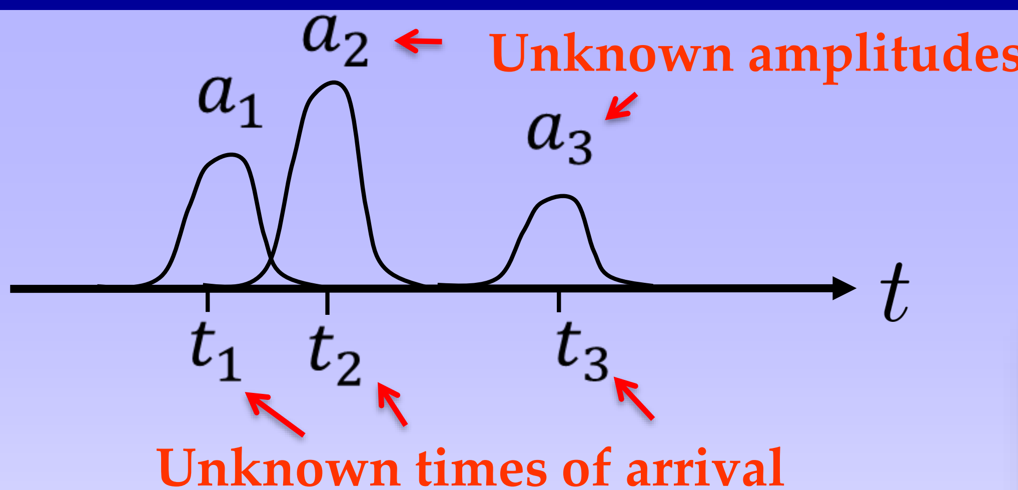
-    

- Multiband Communication



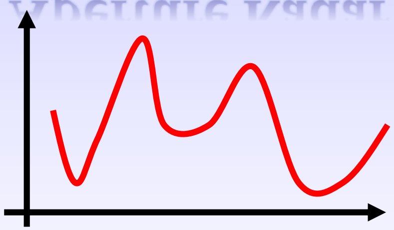
- Can be viewed as $f_{\max}-$bandlimited
- But sampling at rate $\geq 2 f_{\max}$ is a waste of resources
- For wideband applications Nyquist sampling may be infeasible

Streams of Pulses

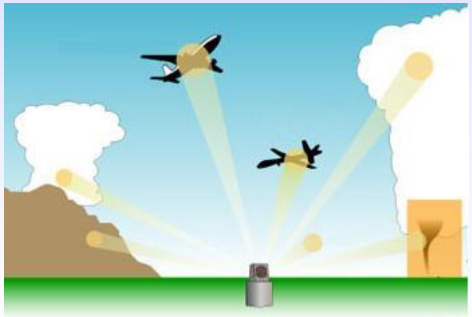


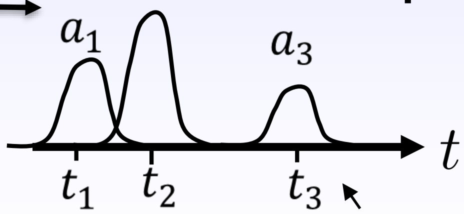
Automotive Radar

Synthetic Aperture Radar



- Radar:



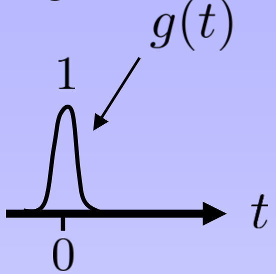


Ultrasound

- Relatively simple, radiation free imaging

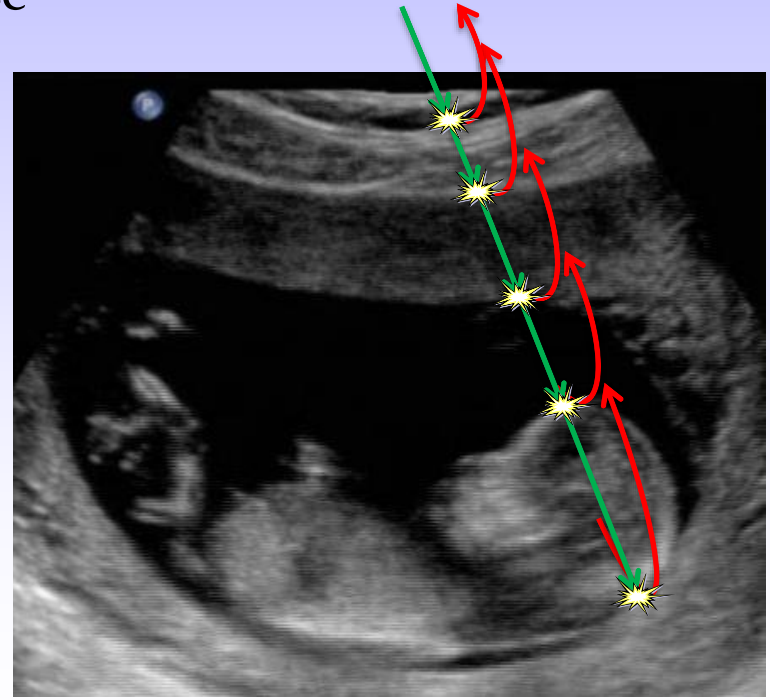
Cardiac sonography

Obstetric sonography

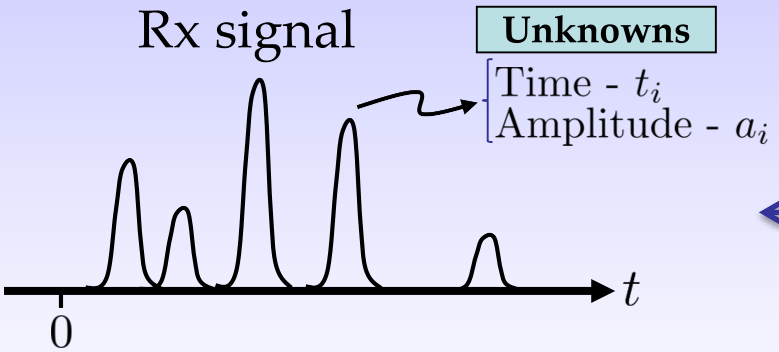


Tx pulse

Ultrasonic probe



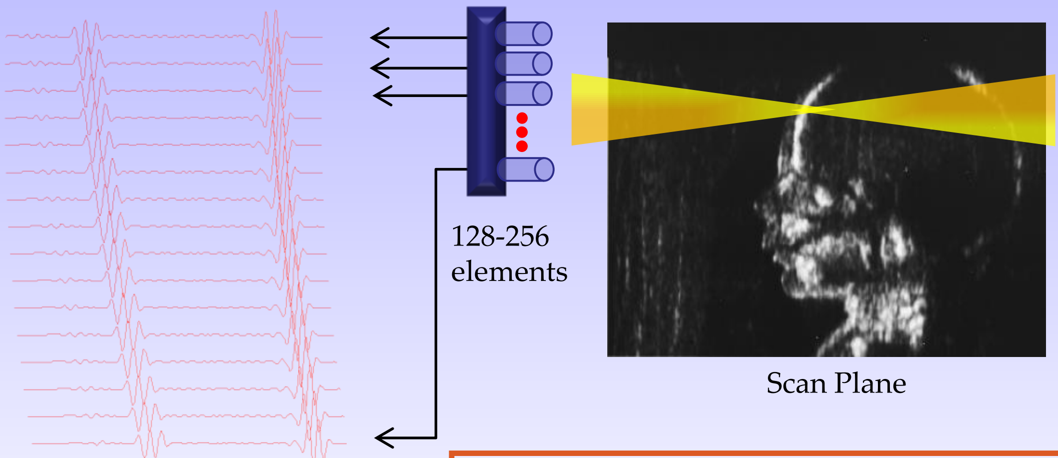
Rx signal



- Echoes result from scattering in the tissue
- The image is formed by identifying the scatterers

Processing Rates

- To increase SNR and resolution an antenna array is used
- SNR and resolution are improved through beamforming 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 rates and large data processing rates
- One image trace requires 128 samplers @ 20M, beamforming to 150 points, a total of 6.3×10^6 sums/frame

Challenges

- Can we reduce analog sampling rates?
- Can we perform nonlinear beamforming on the sub-Nyquist samples without interpolating back to the high Nyquist-rate grid digitally?

Compressed Beamforming

Goal: reduce ultrasound machine size at same resolution

Enable 3D imaging

Increase frame rate

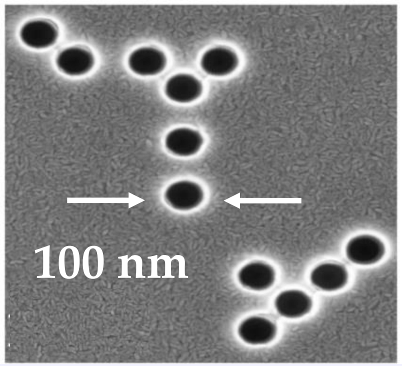
Enable remote wireless ultrasound

Subwavelength Imaging + Phase Retrieval

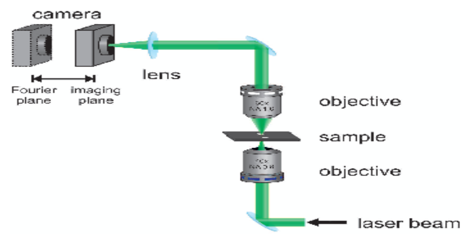
Collaboration with the groups of Moti Segev and Oren Cohen

- Diffraction limit: The resolution of any optical imaging system is limited by half the wavelength
- This results in image smearing
- Furthermore, optical devices only measure magnitude, not phase

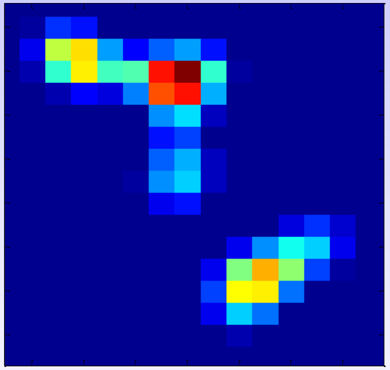
λ=514nm



Nano-holes
as seen in
electronic microscope



Sketch of an optical microscope:
the physics of EM waves acts
as an ideal low-pass filter



Blurred image
seen in
optical microscope

Sparsity Based Subwavelength CDI

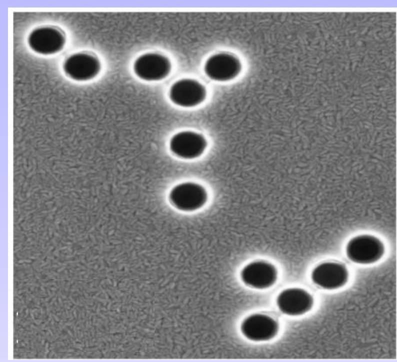
Szameit et al., Nature Materials, 12

- Overcome both the lowpass filter and phase loss

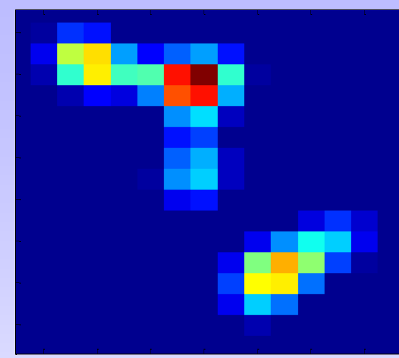
Circles are 100 nm diameter

Wavelength 532 nm

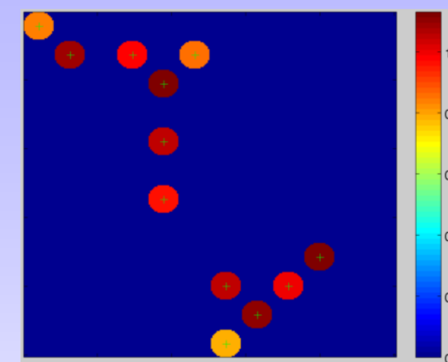
SEM image

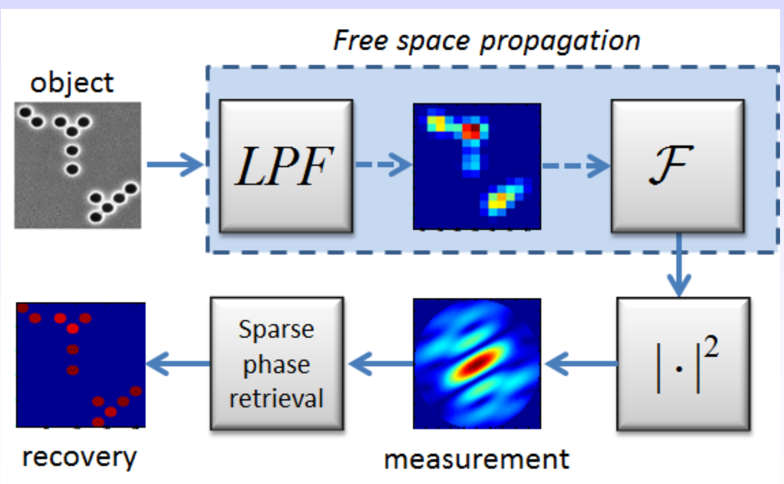


Blurred image



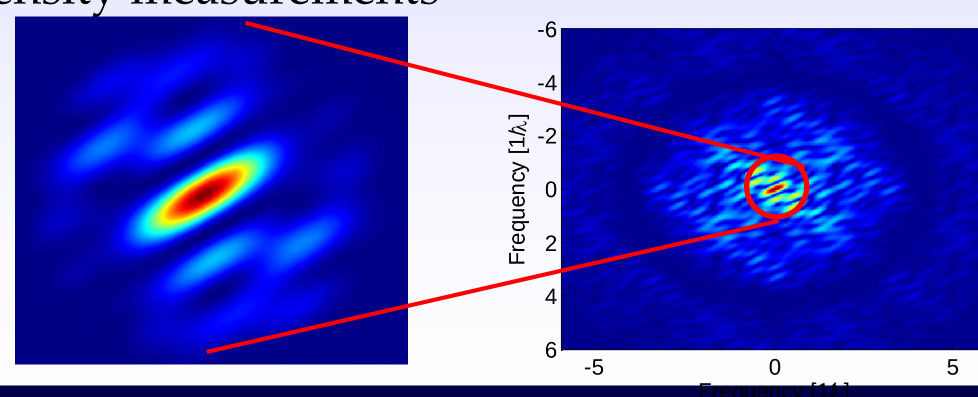
Sparse recovery





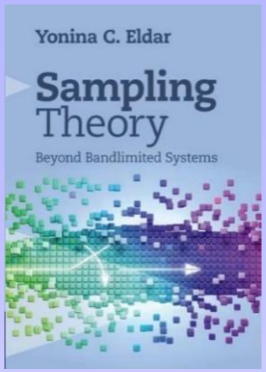
Diffraction-limited (low frequency) intensity measurements

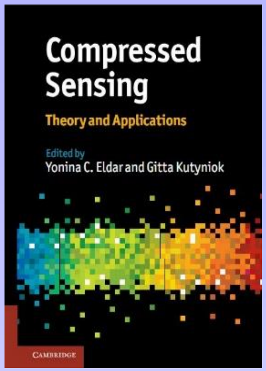
Model Fourier transform

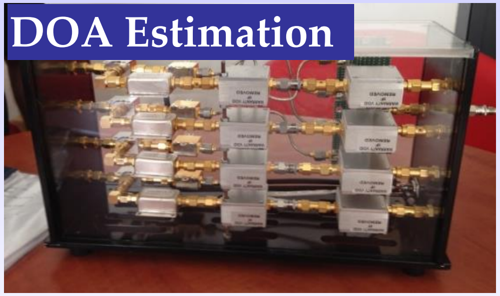


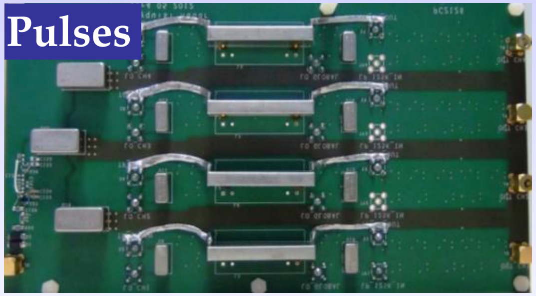
Xampling: Compression + Sampling

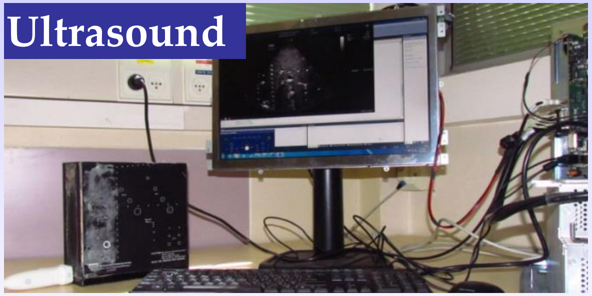
- Xampling: practical sub-Nyquist sampling and processing
- Many examples in which we reduce sampling rate by exploiting structure and goal
- Low rate translates to lower radiation dosage, faster scanning, processing wideband signals, smaller devices and improved resolution

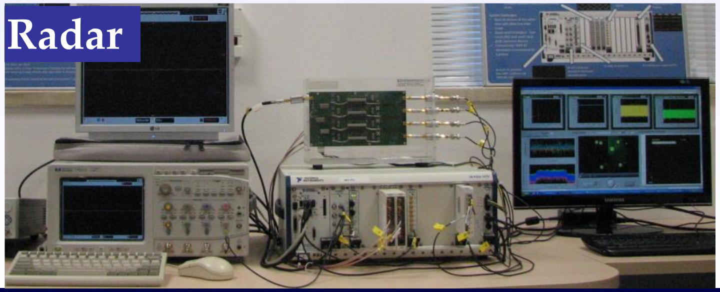


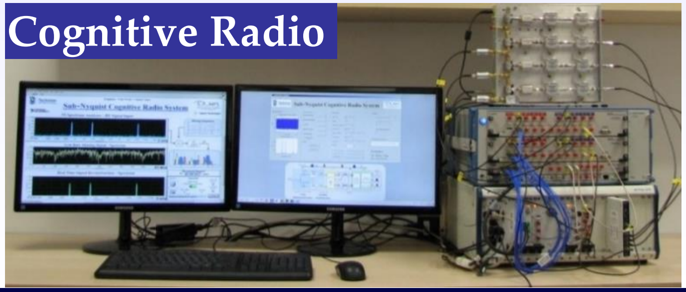












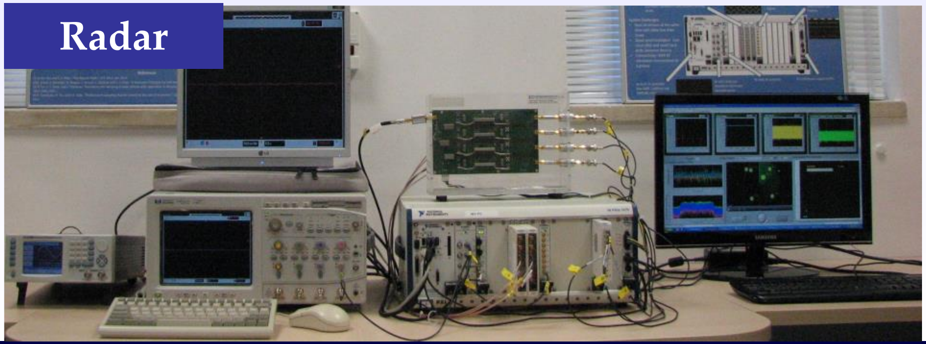
Ultrasound

MRI

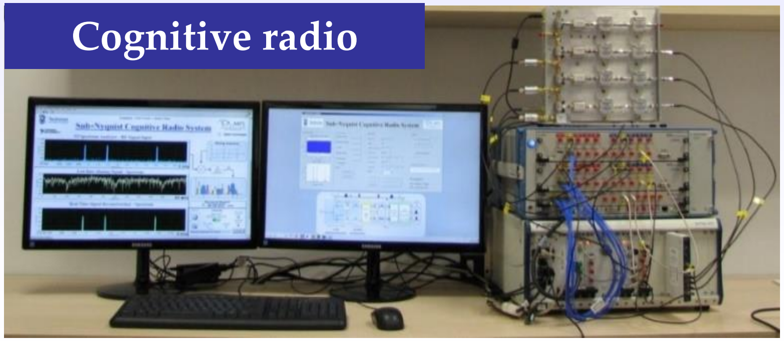
DOA Estimation

Part 2:

Xampling: Reduced rate sampling



Radar



Cognitive radio

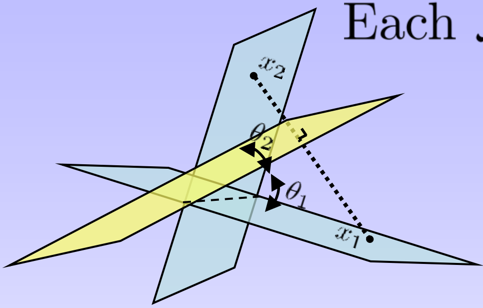
Union of Subspaces

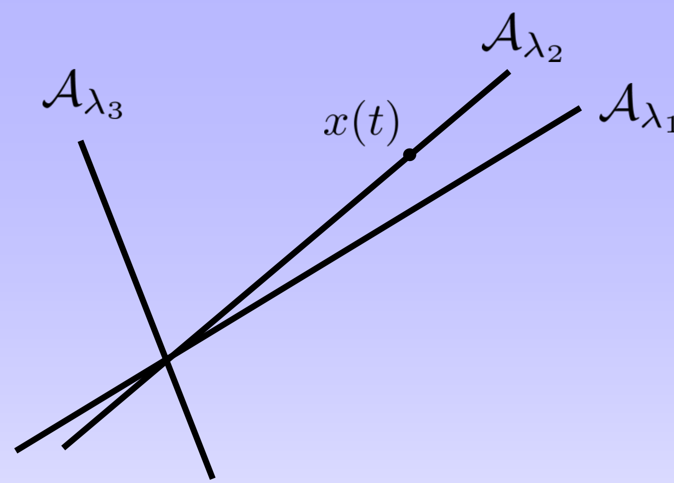
Lu and Do 08, Mishali and Eldar 09

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

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

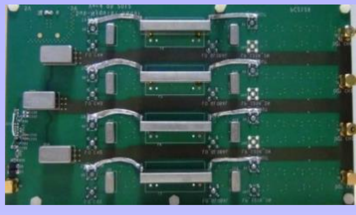
Theorem

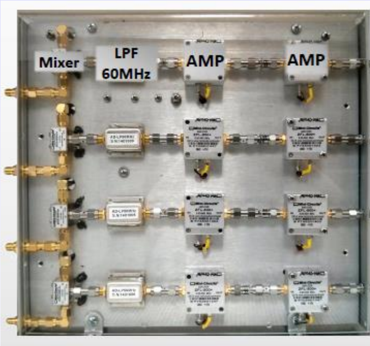
A sampling operator is invertible over a union of subspaces $\mathcal{U}$ if and only if it is invertible for every

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

Xampling:
Compression + Sampling

Mishali and Eldar, 10



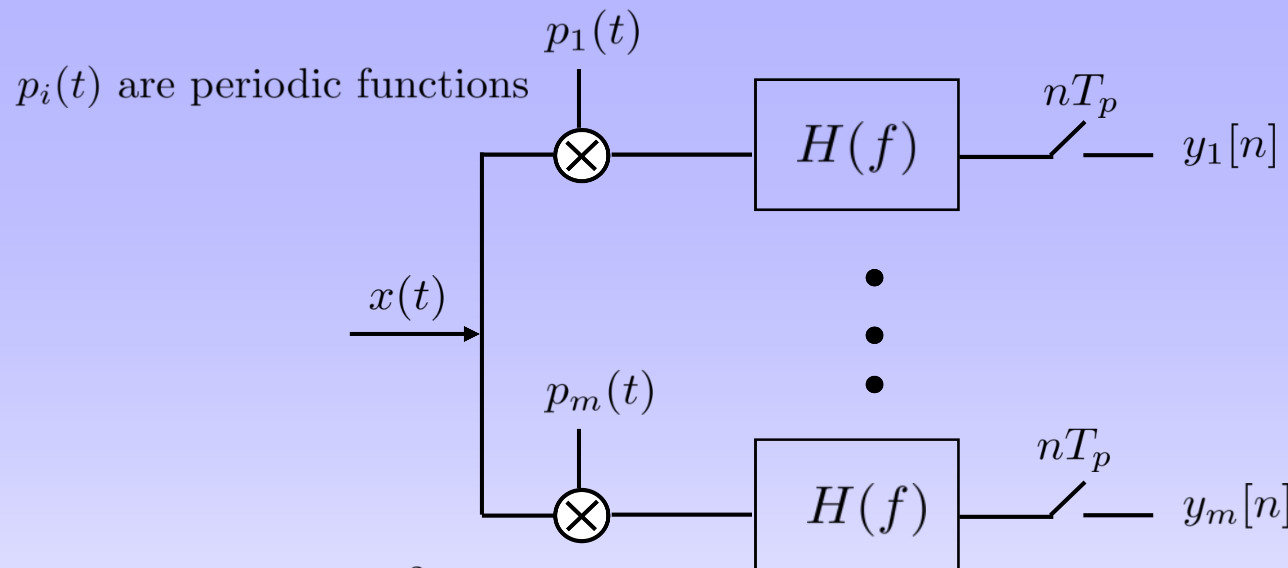


- Prior to analog sampling reduce bandwidth by projecting data onto low dimensional analog space
- Creates aliasing of the data
- Sample the data at low rate using standard ADCs in such a way that in the digital domain we get a CS problem
- Results in low rate, low bandwidth, simple hardware and low 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)**

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

Analog preprocessing　　Low rate (bandwidth)

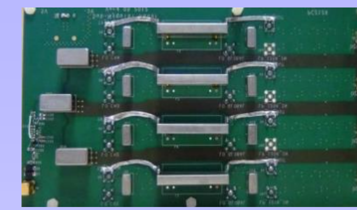
Xampling Hardware

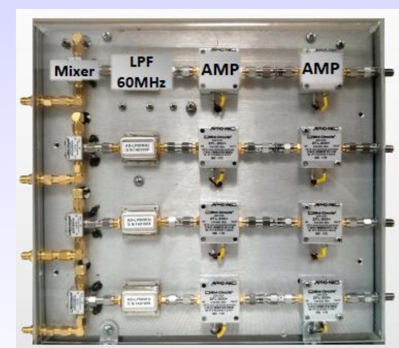


- $p_i(t) = \sum a_{in} e^{-j\frac{2\pi}{T_p}nt}$ sums of exponentials
- The filter *H(f)* shapes the tones and reduces bandwidth
- The channels can be collapsed to a single channel

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

Analog preprocessing   Low rate (bandwidth)

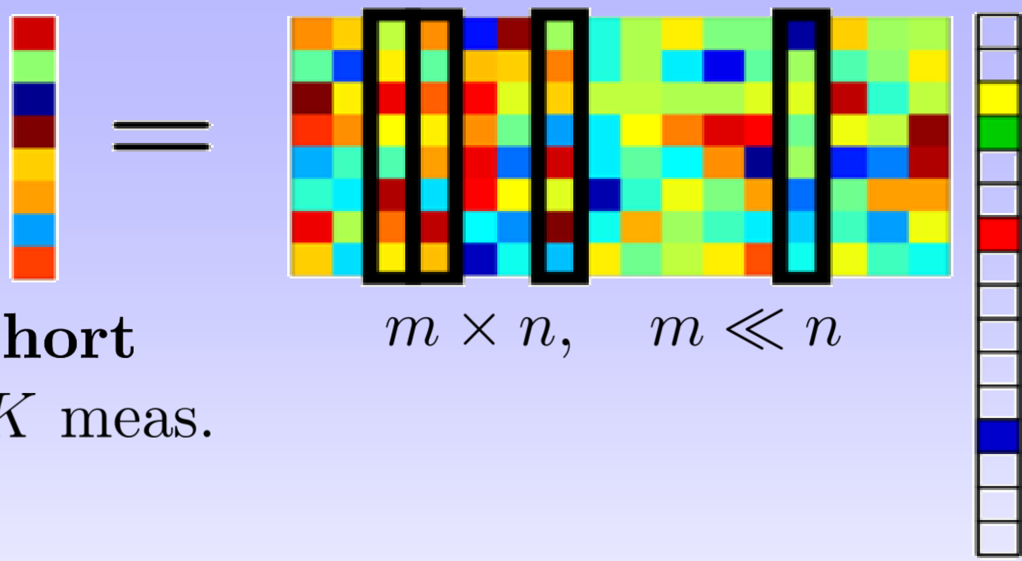


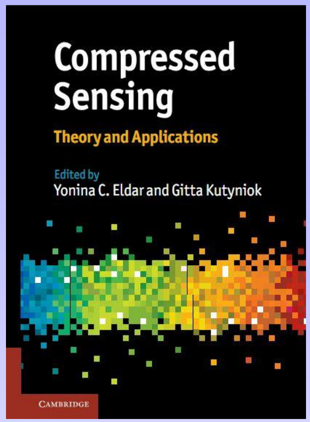


Compressed Sensing

Candes, Romberg, Tau 06, Donoho 06

$\mathbf{y}$ $\quad \boldsymbol{\Phi}$ $\quad \mathbf{x}$





Short

$\approx 2K$ meas.

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

Long

K-sparse

(K nonzeros)

Main ideas:

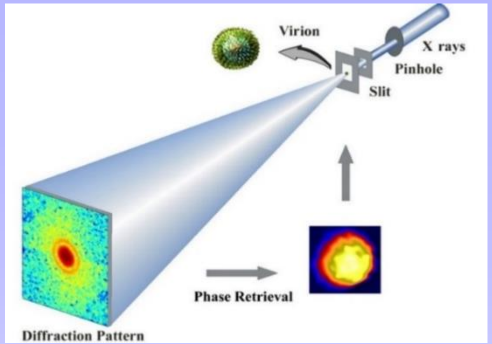
- Sparse input vector with unknown support
- Sensing by sufficiently incoherent matrix (semi-random)
- Polynomial-time recovery algorithms from $K \log n$ measurements
- Modern optimization methods come into play

Compressed Sensing Extensions

- Nonlinear sparse recovery (optics):
  - Phase retrieval

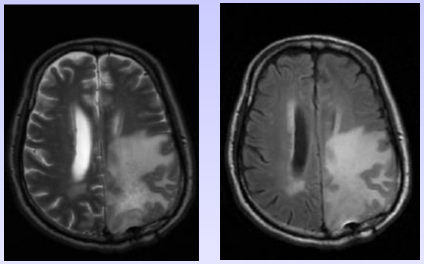
    (Shechtman et. al 11, 14, 15, Eldar and Mendelson 12, Ohlsson et. al 12)
  - Nonlinear compressed sensing

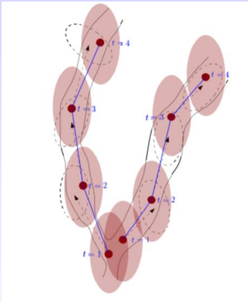
    (Beck and Eldar 12, Bahman et. al 11)



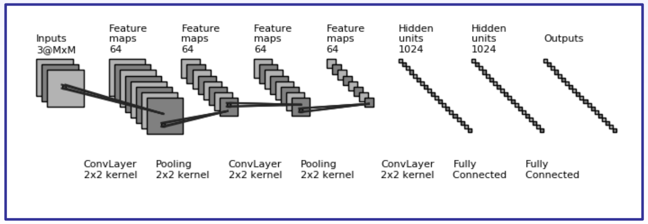
- Reference based sparse recovery (MRI)

  (Weizman, Eldar and Ben Bashat 16)



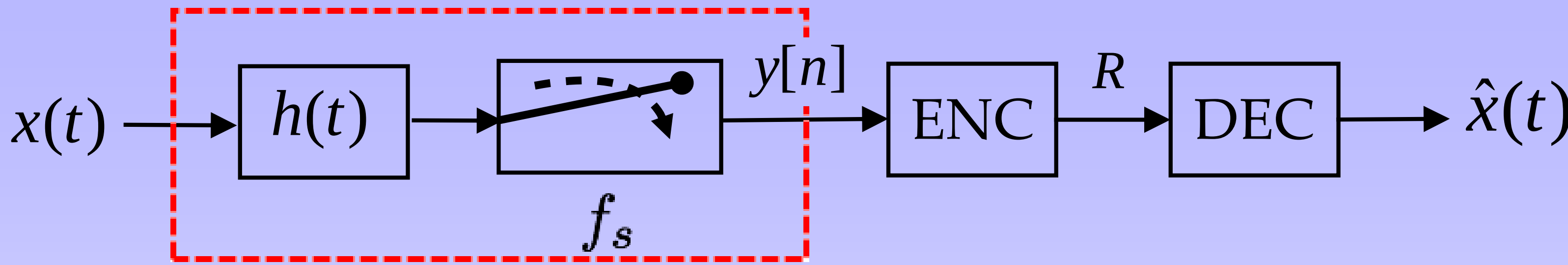


- Sparsity with tracking (ultrasound) (Solomon et. al 18)
- Statistical sparsity (Solomon et. al 18, Cohen and Eldar 17,18)
- Deep learning from compressed samples



Analog Source Coding

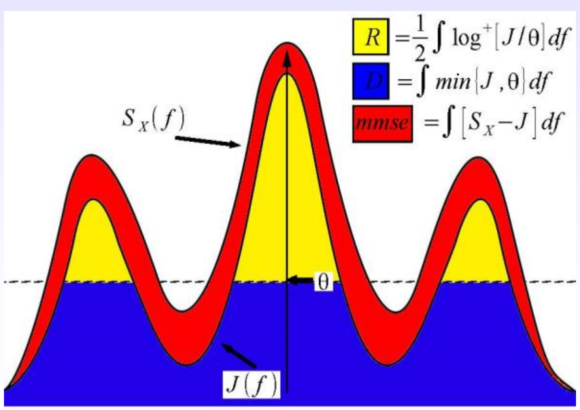
Kipnis, Goldsmith and Eldar 17



Sampler

$$\inf_{f_s} D(f_s, R) = \inf \left\| x(t) - \hat{x}(t) \right\|^2$$

- For a continuous signal *x(t)* and bit rate *R* what is the minimum possible distortion ?
- What is the minimum sampling rate that achieves this distortion?

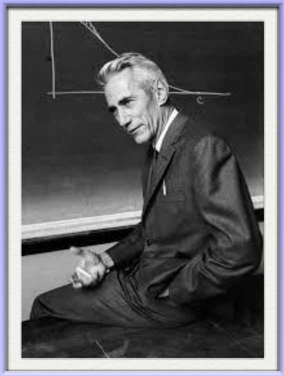


Analog source coding theorem

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

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

Optimal Sampling Rate



Shannon [1948]:

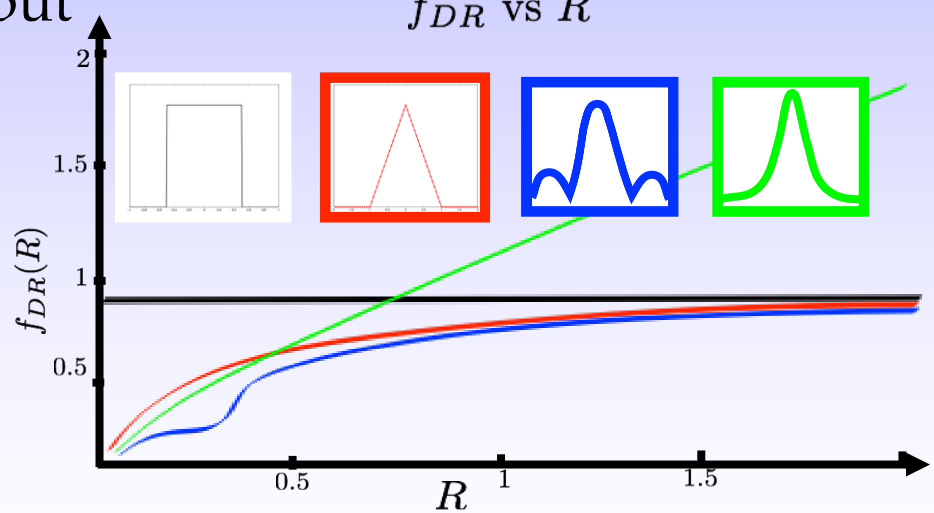
"we are not interested in exact transmission when we have a continuous source, but only in transmission to within a given tolerance"

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

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

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

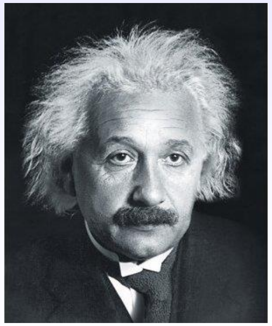
$$f_s \geq f_{DR}(R)!$$



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

Part 3:

Applications to Comm, Radar and Ultrasound

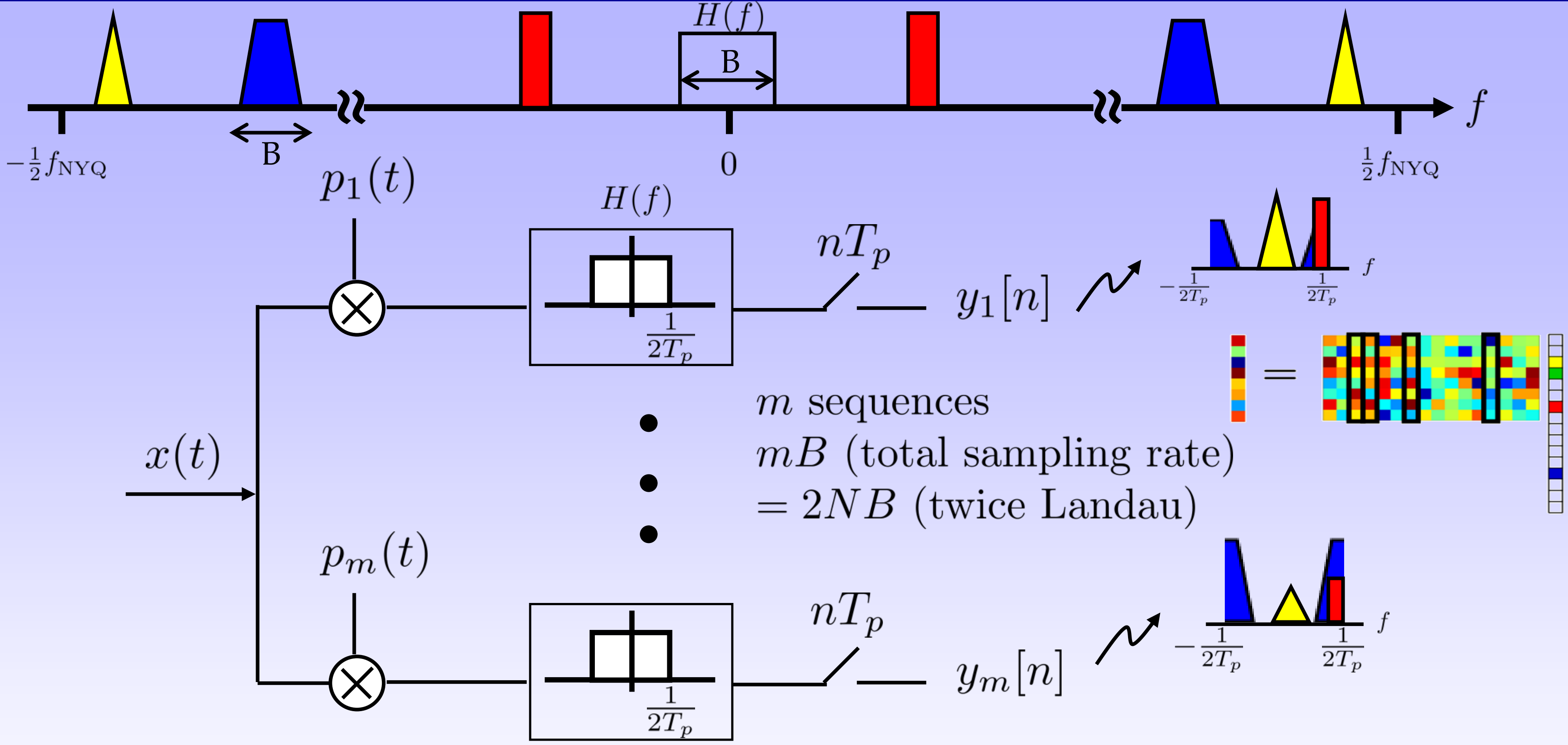


"In theory, theory and practice are the same.
In practice, they are not."

Albert Einstein

The Modulated Wideband Converter

Mishali and Eldar, 11



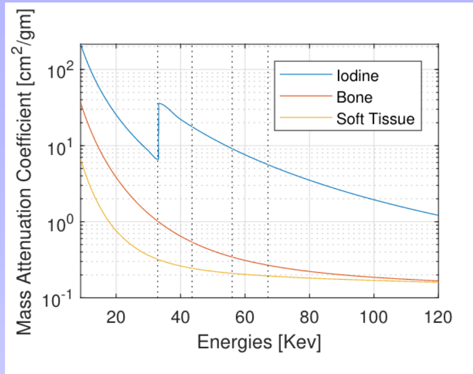
T_p−periodic $p_i(t)$ gives the desired aliasing effect

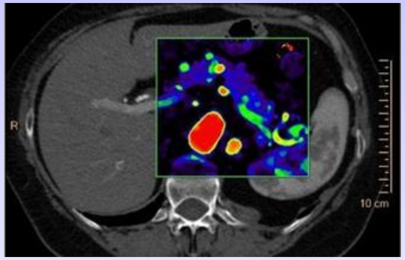

Technion
Israel Institute of Technology
Headed by Yonina Eldar
S_A_MPL
Signal Acquisition Modeling and Processing Lab
Sub-Nyquist
Cognitive Radio System

Spectral CT – with Pseudo-Polar Transform

Tsiper and Eldar 2018

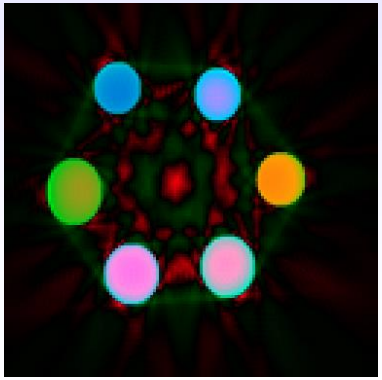
- Separate materials based on spectral properties
- Transforming the spectral scan with RAPToR to the pseudo-polar grid
  - Better algebraic stability
  - Lower computational complexity
- New iterative algorithm for spectral decomposition
- Results out perform state-of-the-art in image quality



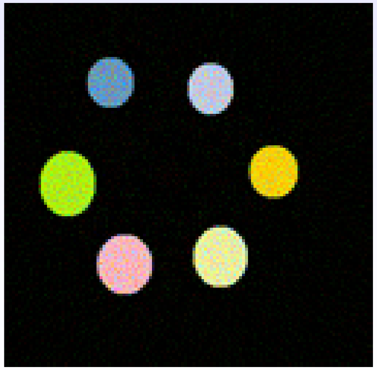


Original Phantom

Traditional Reconstruction SNR = 80dB



Our Method SNR = 40dB

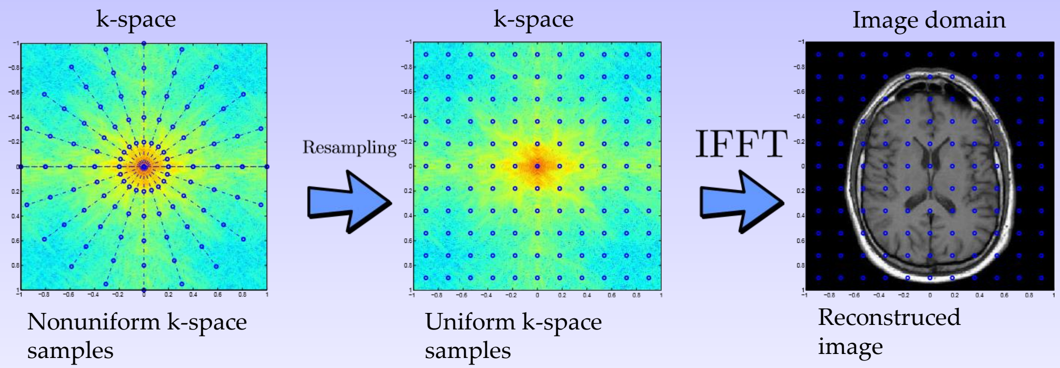


Simulation Parameter	Value
Tube Voltage	120 keV
# Energy Bins	3
Basis Materials	Iodine, Calcium, Soft Tissue
SNR	40 dB

SPURS: SParse Uniform ReSampling

Kiperwas, Rosenfeld and Eldar 16

- When sampling non-uniformly one needs to interpolate to a uniform grid to apply FFT
- Particularly true when undersampling using non-Cartesian grids



- Conventional resampling is computationally demanding (NUFFT) **(Fessler and Sutton 03)**
- SPURS: Solution based on modern sampling methods and signal priors
- Efficient implementation using sparse system solvers and filtering

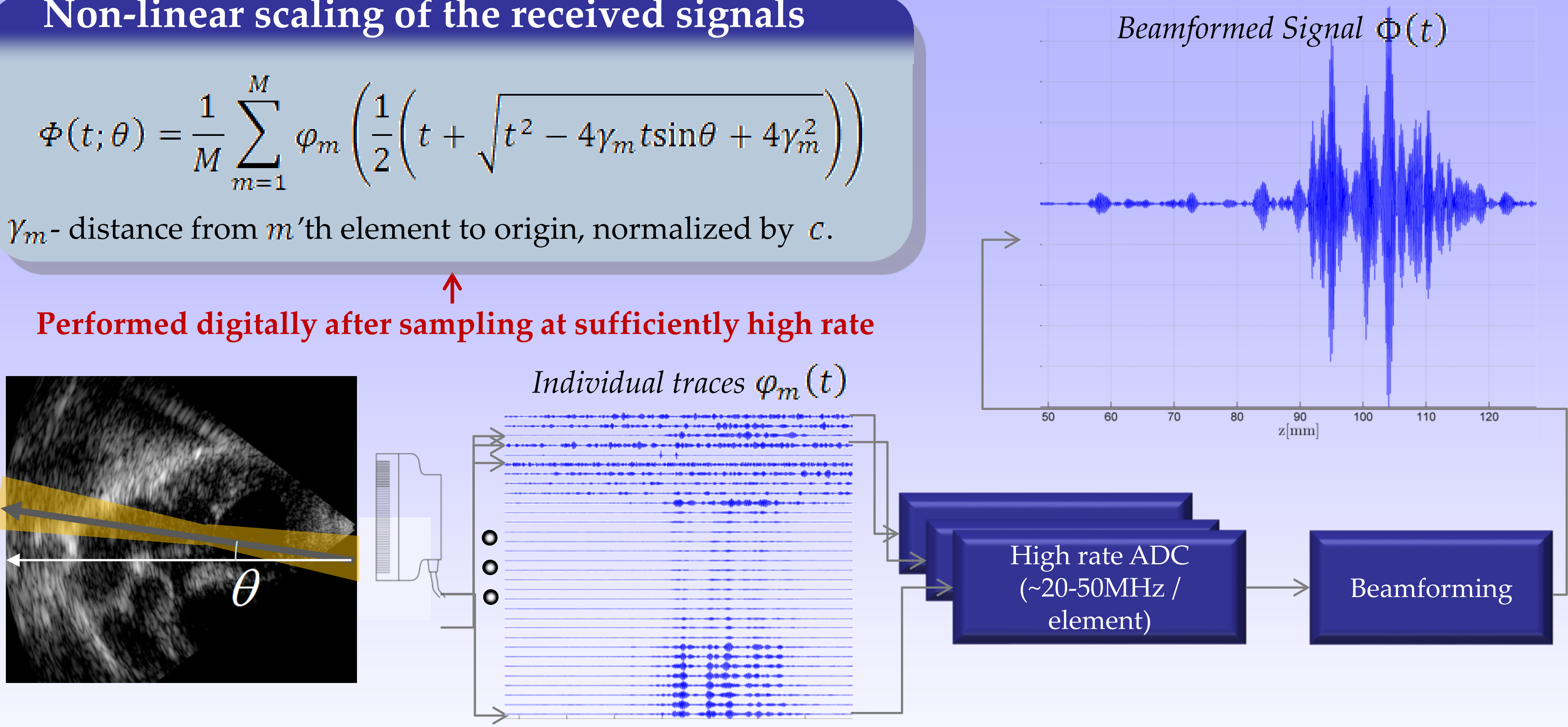
Conventional Beamforming

Non-linear scaling of the received signals

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

γ_m - distance from m'th element to origin, normalized by c.

Performed digitally after sampling at sufficiently high rate



- **Focusing along a certain axis – reflections originating from off-axis are attenuated (destructive interference pattern)**
- **SNR is improved**

Compressed Beamforming

Chernyakova and Eldar, 14

- Each individual trace is buried in noise and has no structure
- Structure exists only after beamforming
- How can we perform beamforming on low rate data? How can we obtain small time shifts without interpolation?

- **Compressed beamforming: Enables beamforming from low rate samples**
- **Key idea: Perform beamforming in frequency**

$$c_k = \frac{1}{M}\sum_{m=1}^{M}\sum_{n}\varphi_m[n]Q_{k,m;\theta}[k-n]$$

Fourier coefficient of BMF signal

Fourier coefficient of signal at element m

Logic:

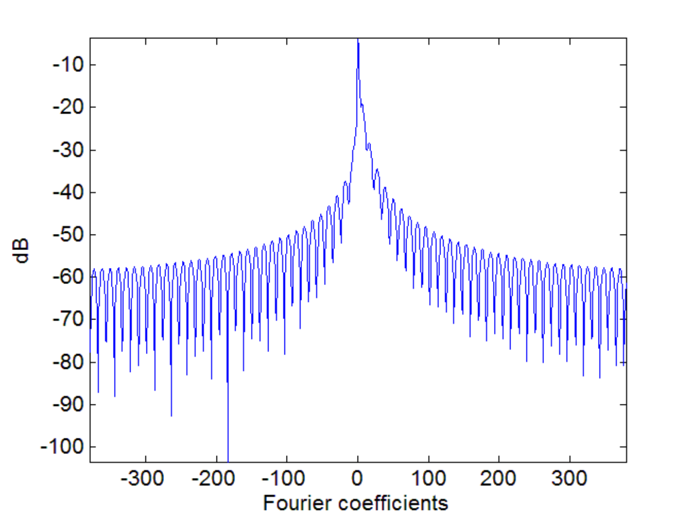
1. BMF signal is a stream of pulses => can be recovered from a small number of c_k
2. Small number of c_k requires only a small number of $\varphi_m[n]$

Low rate sampling of $\varphi_m(t)$!

$Q_{k,m;\theta}[n]$ are the Fourier coefficients of $q_{k,m}(t;\theta)$

$$q_{k,m}(t;\theta) = I_{[\delta_m/c,\tau_m(T,\theta)]}(t)\left(1+\frac{(\delta_m/c)^2\cos^2\theta}{(t-(\delta_m/c)\sin\theta)^2}\right)\times$$

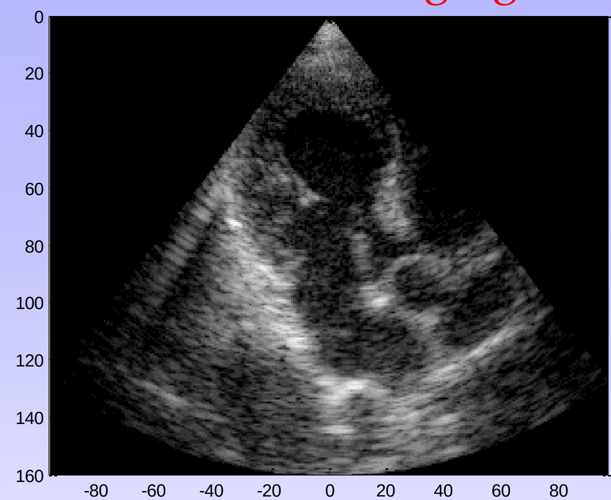
$$\exp\left\{i\frac{2\pi}{T}k\frac{\delta_m/c-t\sin\theta}{(t-\delta_m/c)\sin\theta}\delta_m/c\right\}$$



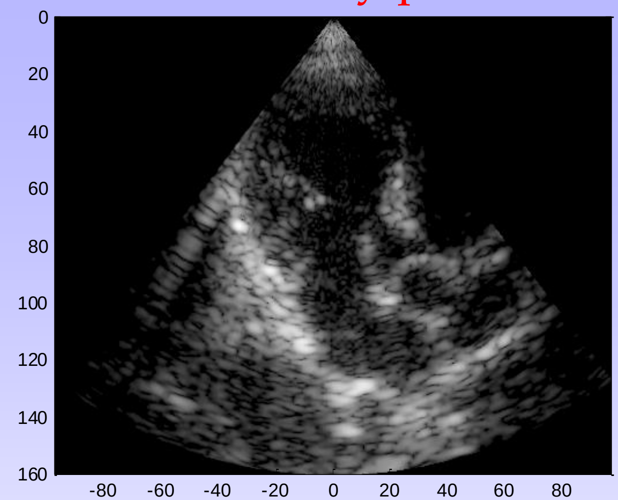
Sub-Nyquist Ultrasound Imaging

Chernyakova and Eldar 13-16

Standard Imaging

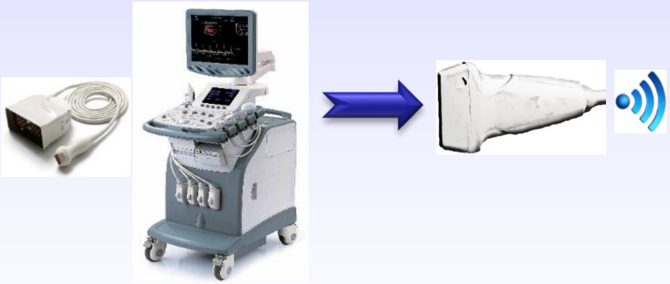


~1/32 of the Nyquist rate



4% Nyquist rate at every channel!

Low rate sampling enables:

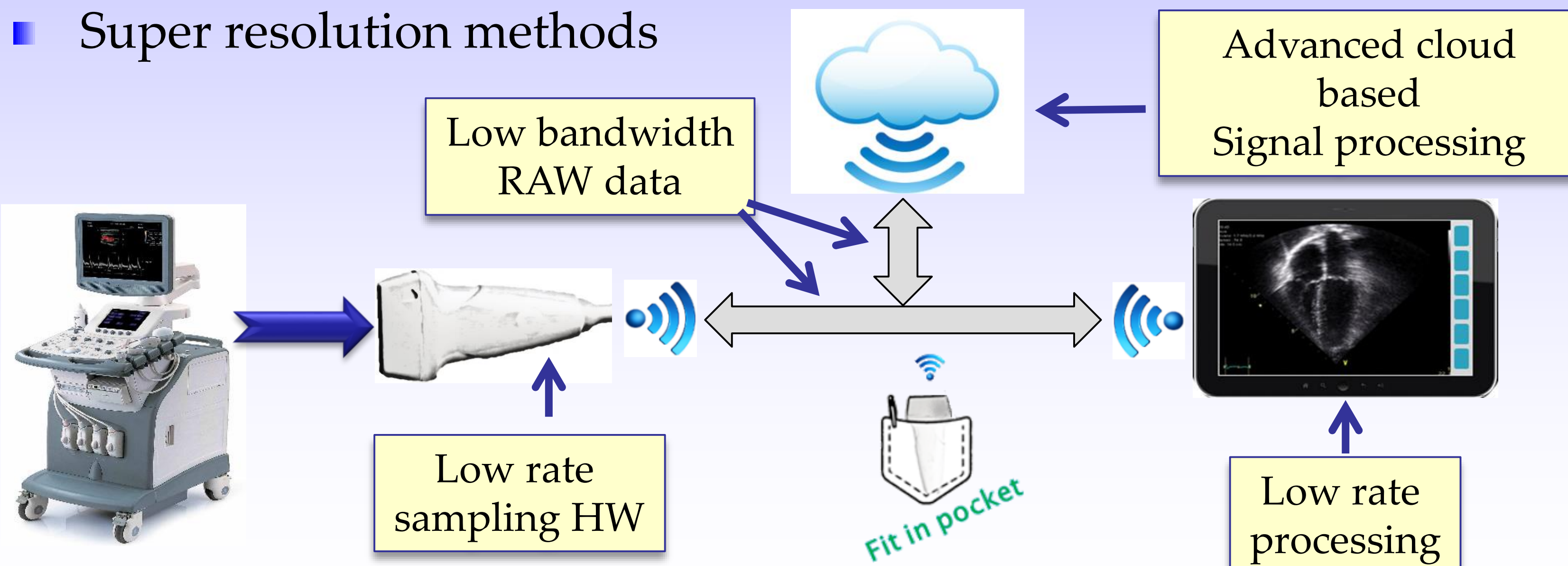


- 3D imaging
- High frame rate for cardiac imaging
- Handheld wireless devices for rural medicine, emergency imaging in the field/ambulance

Bring the Digital Revolution to Ultrasound, Anywhere

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

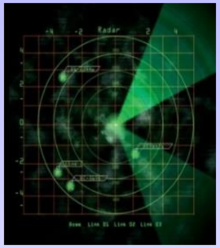
- Allows to integrate electronics into probe: wireless ultrasound
- Enabling an “open imager” – advanced signal processing and ML methods that can run on any platform
- Enabling remote health flexibility
- Super resolution methods

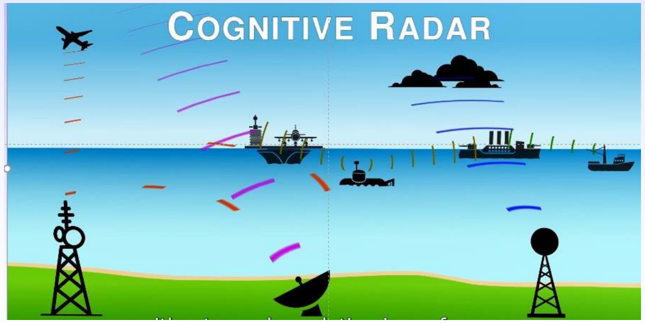


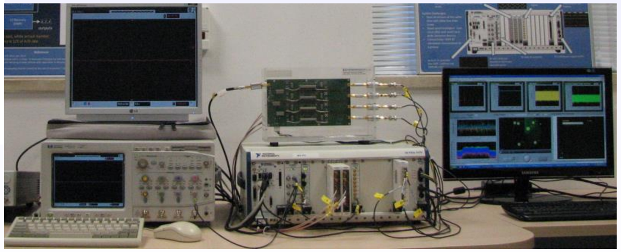
Demo Movie

Defense Applications

- 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



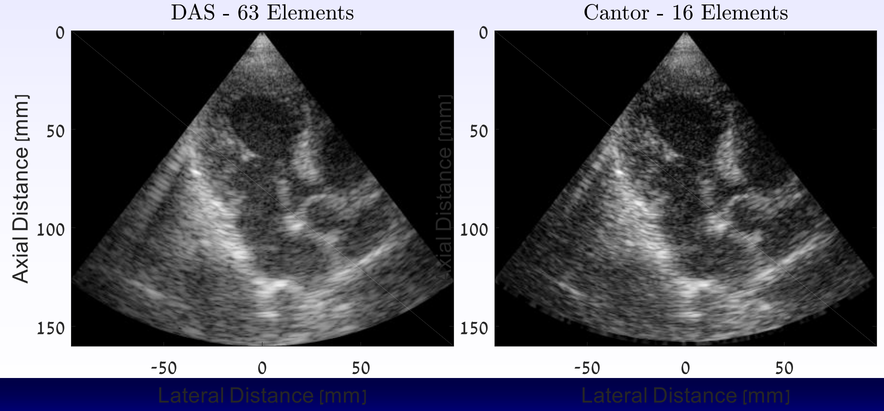


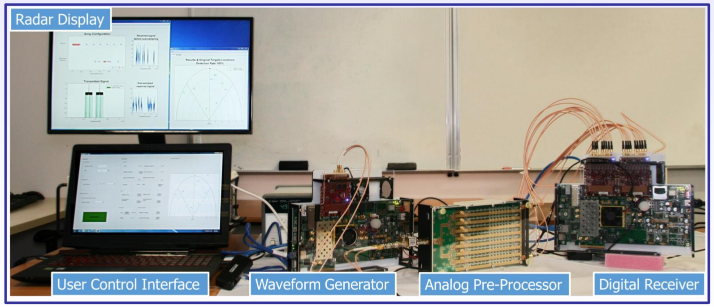


Sub-Nyquist and Cognitive Radar

Part 4:

Spatial subsampling

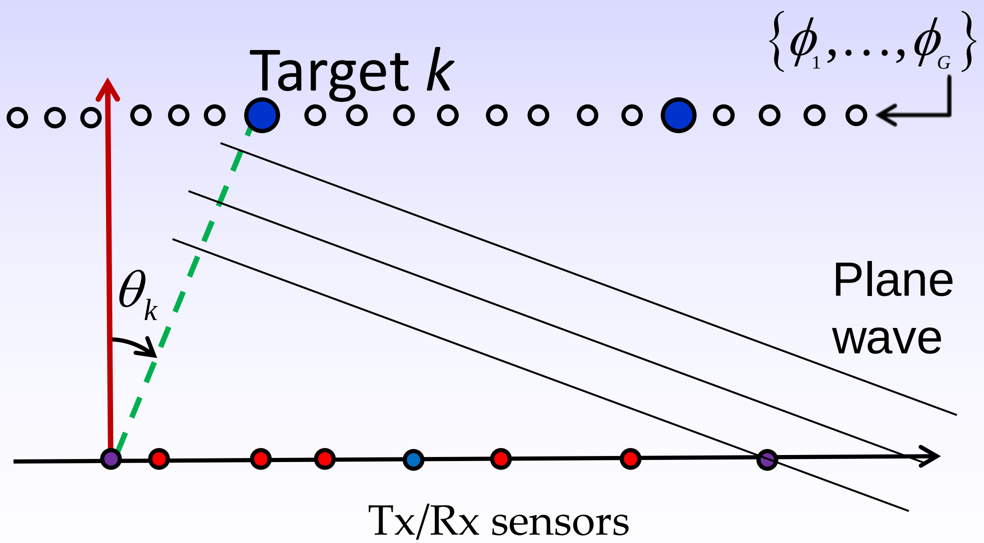




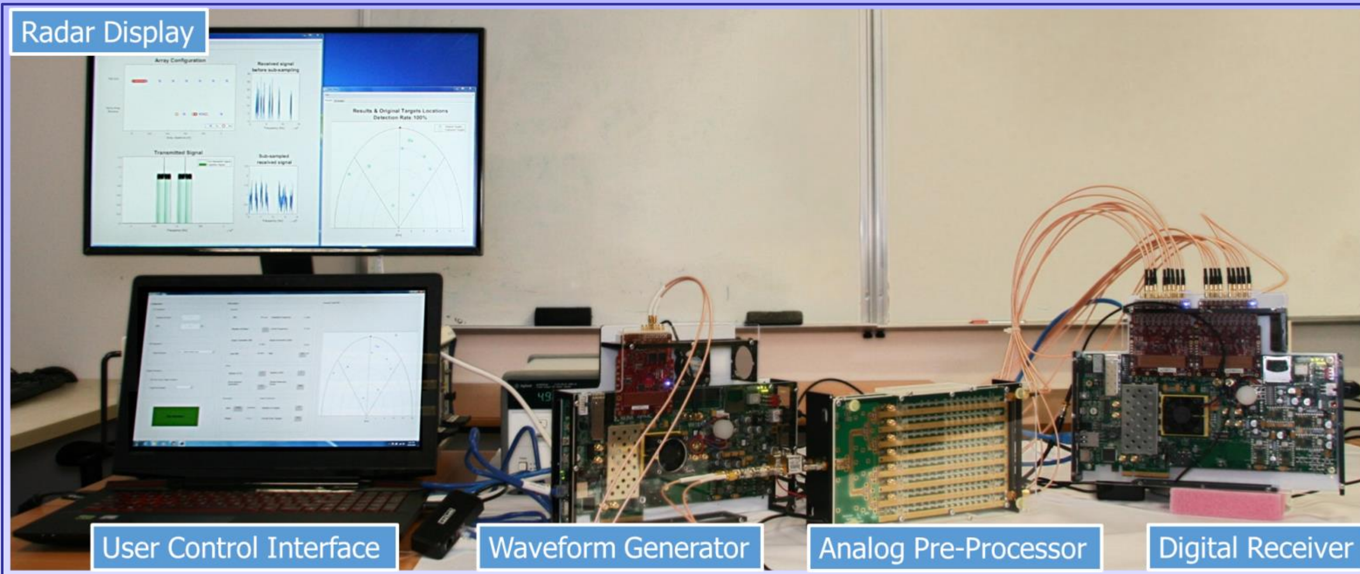
Spatial CS in MIMO Radar

Rossi, Haimovich and Eldar, 13

- We can randomly dilute the number of elements in a MIMO radar using sub-Nyquist and CS ideas
- Using spatial Nyquist sampling the array aperture scales linearly with *MN* – the number of transmit and receive antennas
- Using CS we can get Nyquist resolution with *MN* scaling logarithmically with aperture

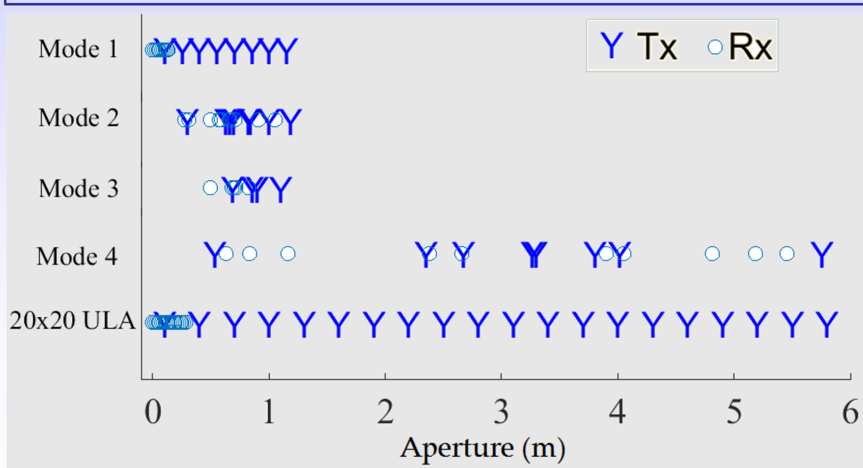


Hardware Prototype



Mishra et al., CoSeRa 2016

Combined temporal and spatial sampling is 12.5% of the Nyquist rate, same resolution



Prototype Modes

Parameters	Mode 1	Mode 2	Mode 3	Mode 4
#Tx, #Rx	8,10	8,10	4,5	8,10
Element placement	Uniform	Random	Random	Random
Equivalent aperture	8x10	8x10	8x10	20x20
Angular resolution (sine of DoA)	0.025	0.025	0.025	0.005
Range resolution	1.25 m			
Signal bandwidth per Tx	12 MHz (15 MHz including guard-bands)			
Pulse width	4.2 μs			
Carrier frequency	10 GHz			
Unambiguous range	15 km			
Unambiguous DoA	180° (from -90° to 90°)			
PRI	100 μs			
Pulses per CPI	10			
Unambiguous Doppler	from −75 m/s to 75 m/s			

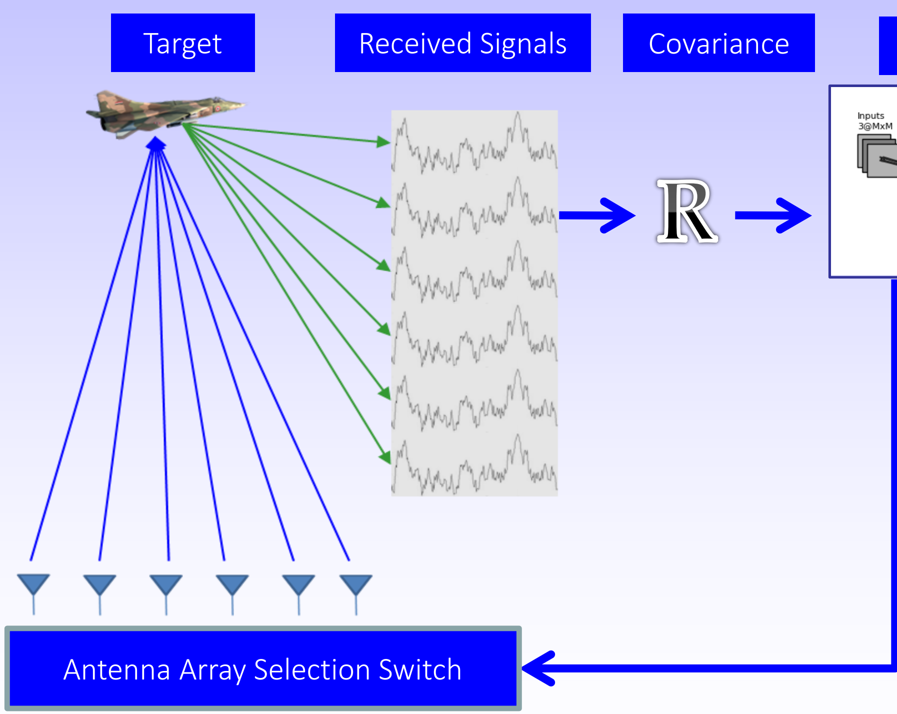
Technical Specifications

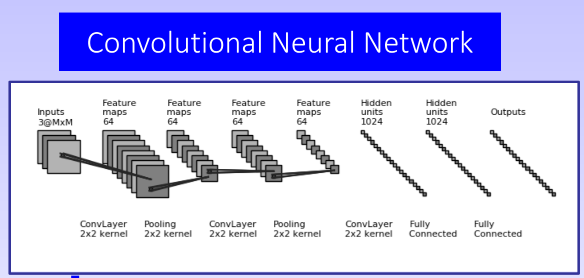
Antenna Selection via Deep Learning

- Standard approach is to choose elements at random
- Can we do better?

Elbir, Mishra and Eldar, 2018

Deep learning:





<u>Our Deep Learning Strategy</u>

- For known target locations can choose arrays that minimize the Cramer-Rao (or other) bound
- **Training data**: for a set of known target locations create **R** and pair with optimal subarrays
- **Train CNN:** to minimize misclassification of determining optimal array
- **Cognitive performance**: For every covariance input, redesign optimal array using trained CNN

Antenna Selection for Imaging

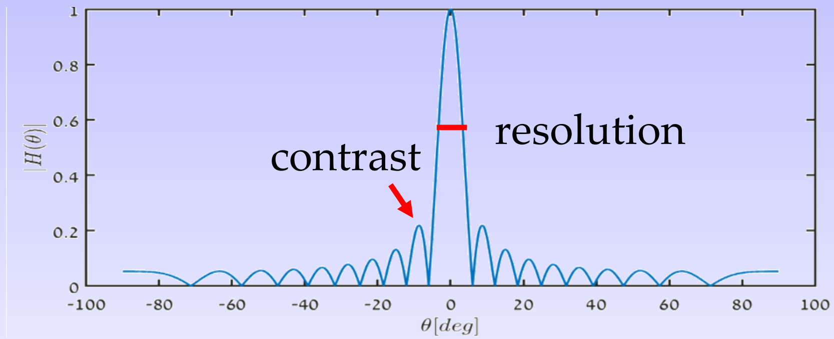
Cohen and Eldar, 2018

- For imaging (radar, ultrasound) there isn't a single metric
- Image quality is determined by the beampattern $H(\theta)$ which represents the directivity of the beamformer and is given by

$$H(\theta) = \sum_n e^{-2\pi j \frac{\sin(\theta)}{\lambda} nd}$$

θ - direction

λ - wavelength of input field



- Can we create the same beampattern with less elements?
- Factorization – create beampattern by a convolution of two functions
  - In active sensing: convolve transmit and receive apertures
  - In passive sensing: convolve receive aperture with itself

Convolutional Beamforming

Convolutional Beamforming (COBA)

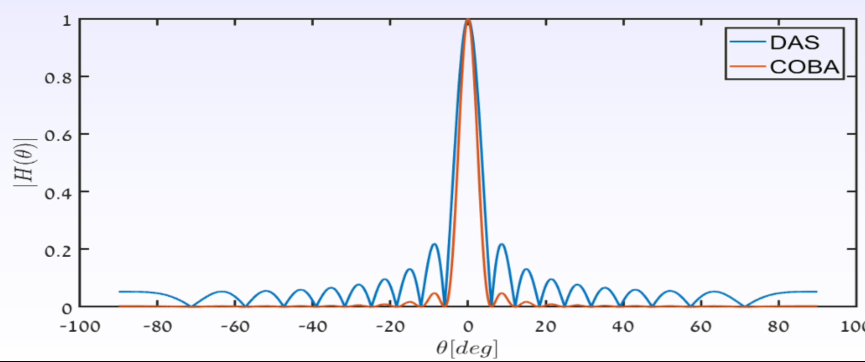
- Output of a standard delay and sum beamformer:

$$b = \sum_{n=-N}^{N} z_n \text{ where } z_n \text{ are the array signals after delays}$$

- Convolutional beamformer (COBA):
  - Compute $y_n = \text{sign}(z_n)\sqrt{|z_n|}$
  - Convolve $\mathbf{s} = \mathbf{y} * \mathbf{y}$
  - Sum $b = \sum_{n=-2N}^{2N} s_n$

- The resulting beam pattern is

$$H(\theta) = \sum_{n=-\mathbf{2}N}^{\mathbf{2}N} \big(2N - |n|\big) e^{-2\pi j \frac{\sin(\theta)}{\lambda} nd}$$



Product Arrays

- Beampattern of COBA can be written by the convolution theorem as

$$H(\theta) = \left(\sum_{n=-N}^{N} e^{-2\pi j \frac{\sin(\theta)}{\lambda} nd} \right) \left(\sum_{n=-N}^{N} e^{-2\pi j \frac{\sin(\theta)}{\lambda} nd} \right) = \sum_{n=-N}^{N} \sum_{m=-N}^{N} e^{-2\pi j \frac{\sin(\theta)}{\lambda} \boxed{(\mathbf{n}+\mathbf{m})} d}$$

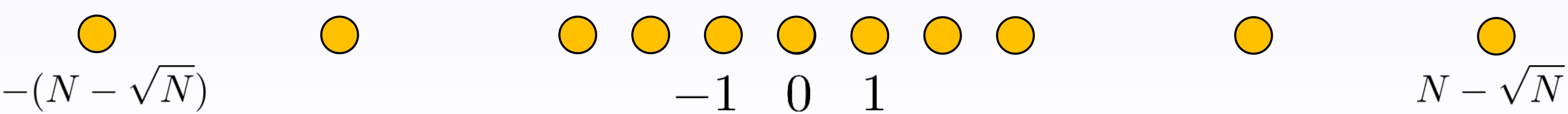
- Applying COBA is equivalent to a delay-and-sum on the sum co-array

$$S = \{n : \quad n = i + j, \quad i, j \in I\}$$

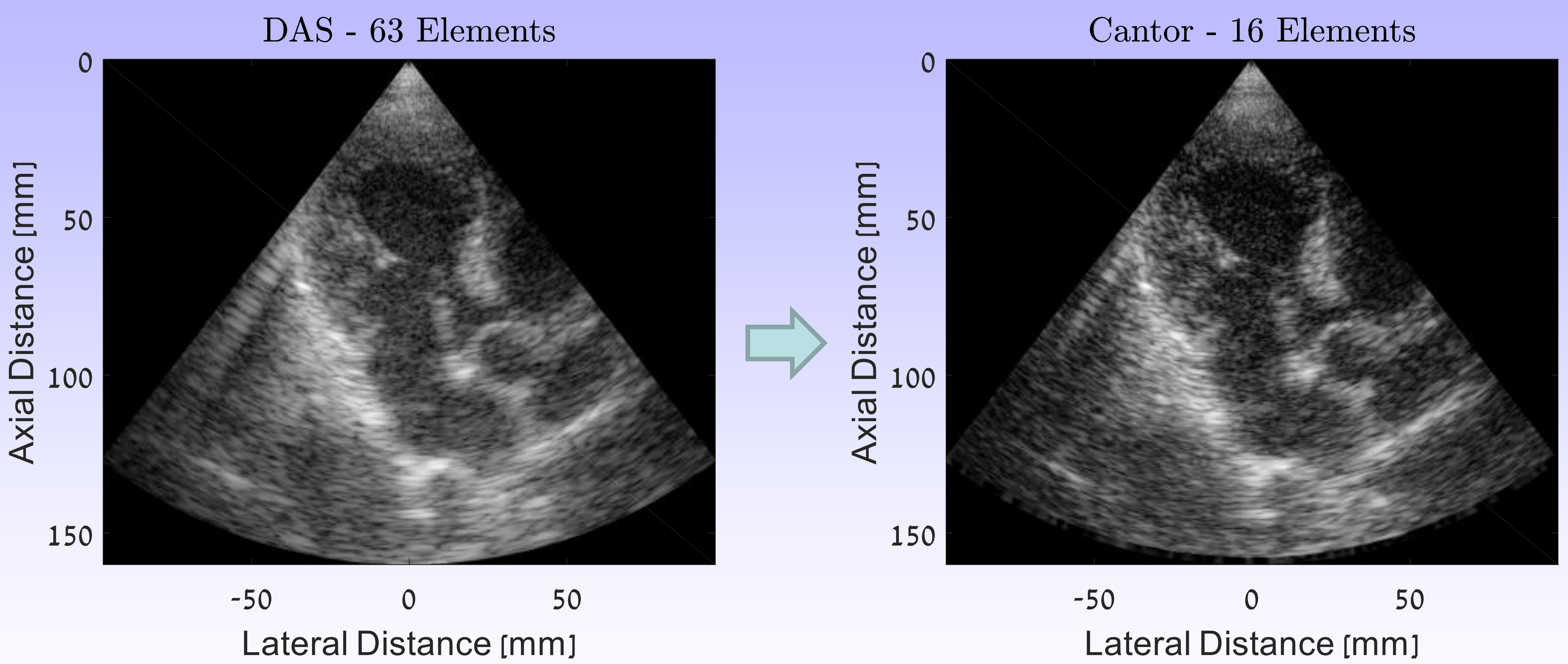
I – location set of the array

- Performance determined by the virtual co-array!
- The same sum co-array can be obtained from a sparse physical array where the number of elements is $2\sqrt{N} - 3$.

  Thus, the reduction factor is $(2N-1)/(2\sqrt{N}-3) \approx \sqrt{N}$!

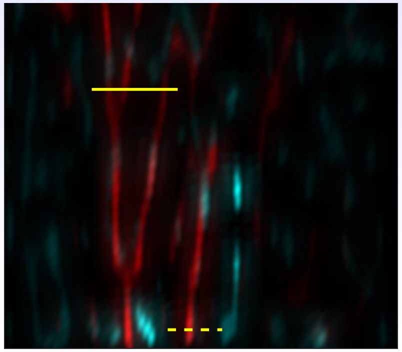


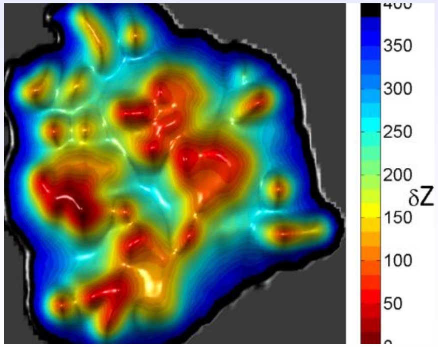
In-Vivo Results

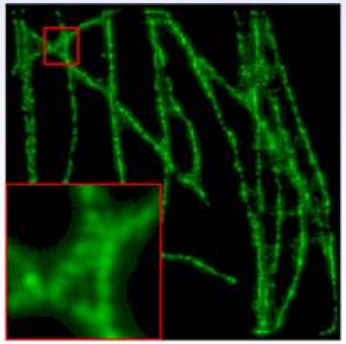


Part 5:

Super-resolution in microscopy and US

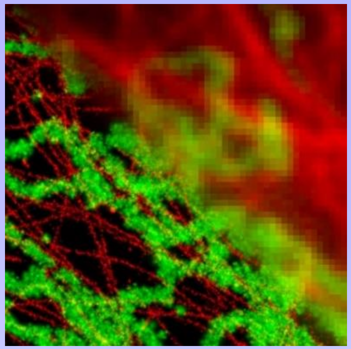






Super Resolution Microscopy

Solomon et. al 18



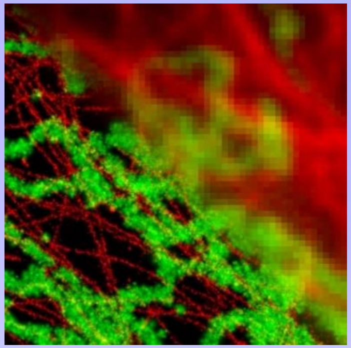
- Spatial resolution is proportional to half the imaging wavelength
- Noble prize 2014: super resolution using optical fluorescence microscopy (Betzig, Hell, Moerner)
- New measurement process – control fluorescence of individual molecules
- Image the same area multiple times – only a few point-emitters each time
- Superimpose the images
- Spatial resolution of ~20nm
- Limited temporal resolution!

> 10000 frames to collect all molecules

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

Correlation-Based Analysis

- For brightness images it is sufficient to estimate the variance of each pixel
- Power spectrum recovery can be performed at much lower rates than signal recovery!
- Translates into fewer images increasing temporal resolution



What is the minimal sampling rate to estimate the signal covariance?

- Assumption: Wide-sense stationary ergodic signal
- For covariance estimation we can substantially reduce the sampling rate even without structure!

Covariance Estimation

Cohen, Eldar and Leus 17

- 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 $r_x(\tau) = \mathbb{E}[x(t)\mathrm{x}(t-\tau)]$

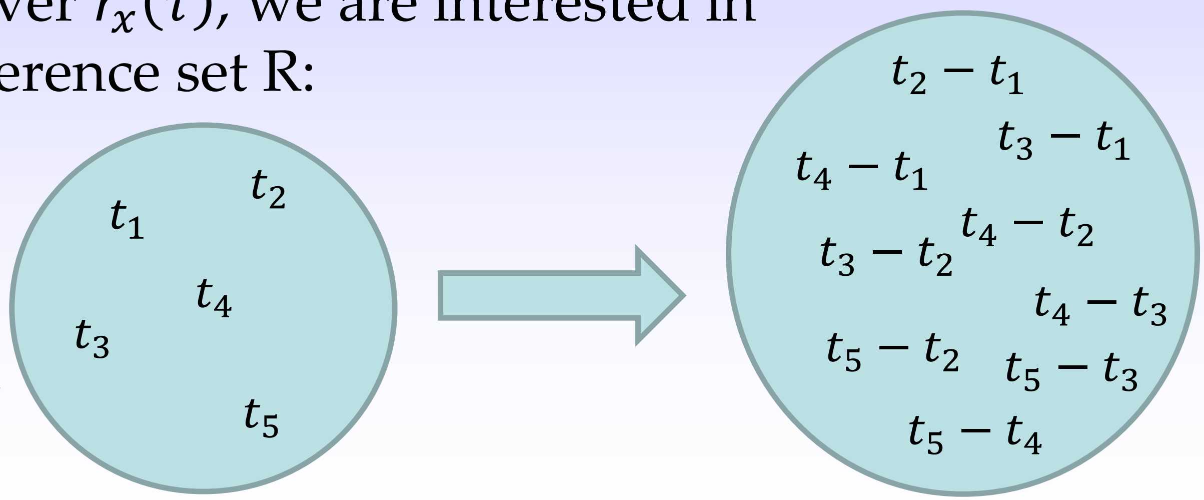
What is the minimal sampling rate to recover $r_x(\tau)$?

- Sub-Nyquist sampling is possible!

Intuition:

- The covariance $r_x(\tau)$ is a function of the time lags $\tau = t_i - t_j$
- To recover $r_x(\tau)$, we are interested in the difference set R:

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



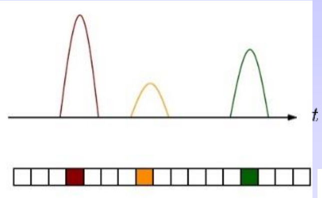
Difference set
$R = \{t_i - t_j\}_{i,j \in \mathbb{Z}}$
$t_i > t_j$

SPARCOM: SPARsity-Based Super Resolution COrrelation Microscopy

Solomon, Mutzafi, Segev, Eldar 18

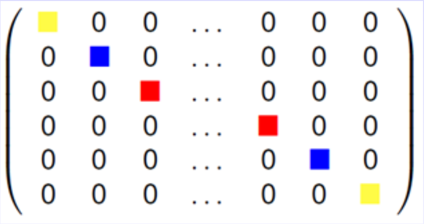
- Take a small number of images with high density of fluorophores
- Compute correlations among images
- Fluorophores in different pixels are independent
- Recover image by estimating the pixel's variances on a high resolution grid

"Relax" the condition for a single emitter per diffraction limited spot



Mathematically:

- Acquired signal: $I(\boldsymbol{r},t) = \sum_{k=1}^{L} u(\boldsymbol{r}-\boldsymbol{r}_k)\, s_k(t)$



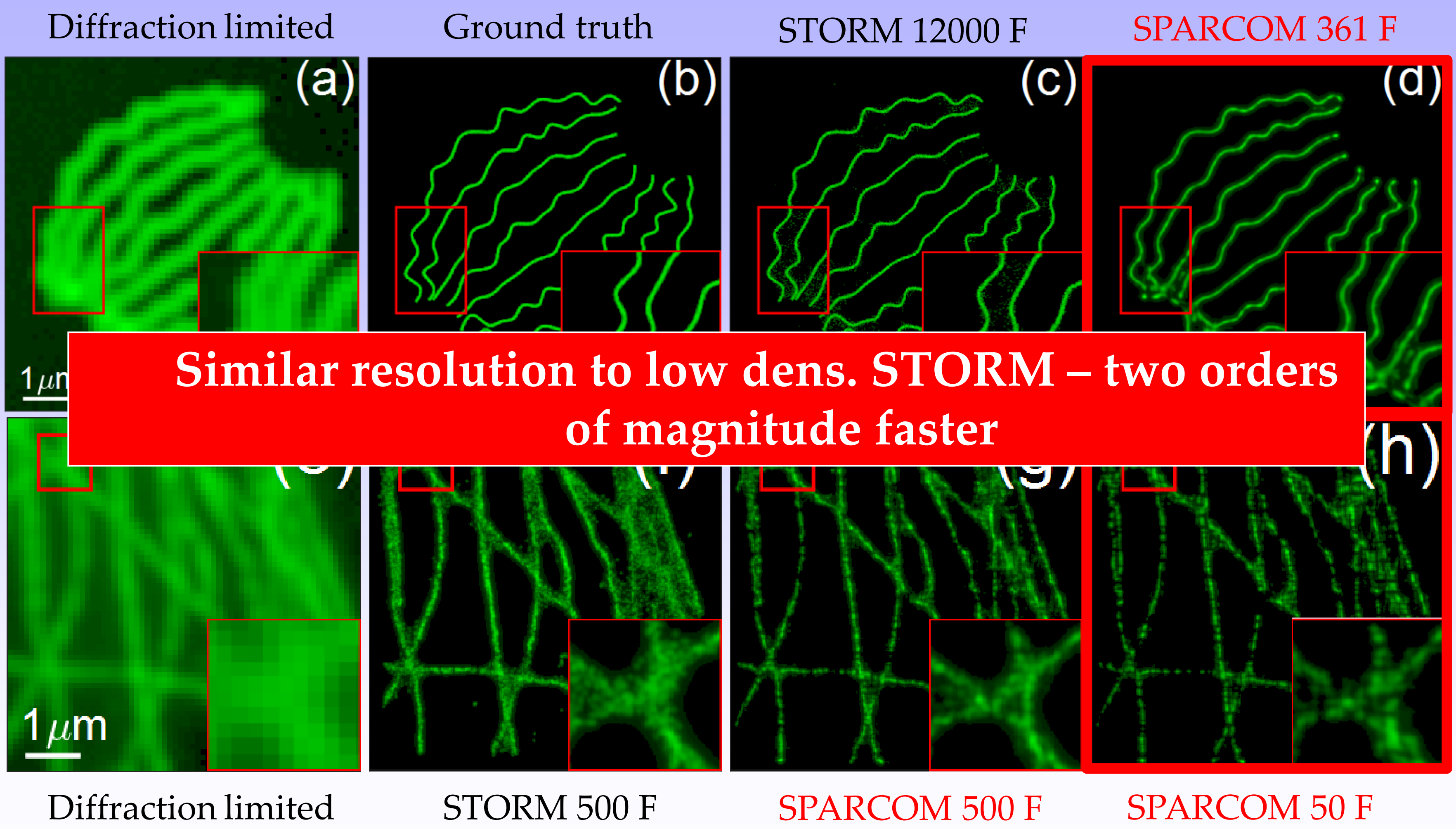
- In correlation space $\boldsymbol{R}_I = \boldsymbol{A}\boldsymbol{R}_s\boldsymbol{A}^H + \boldsymbol{N}$

- Recovery based on Reweighted LASSO minimization

$$\min_{\boldsymbol{r}_s \geq 0} \lambda ||\boldsymbol{W}\boldsymbol{r}_s||_1 + \frac{1}{2}\left\| \boldsymbol{R}_I - \sum_{l=1}^{N^2} a_l a_l^H r_s^l \right\|_F^2$$

SPARCOM: Super Resolution Correlation Microscopy

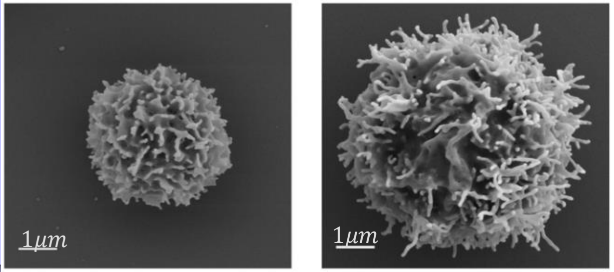
Data taken from: http://bigwww.epfl.ch/smlm/datasets/index.html

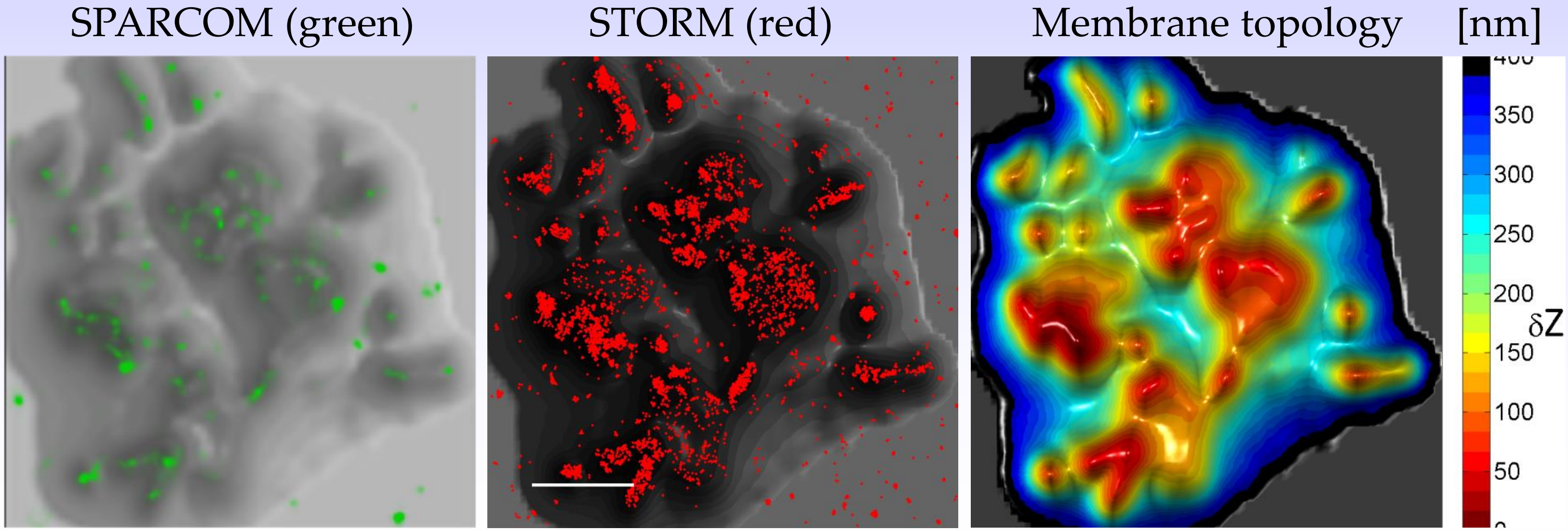


Super-resolution of T-cell Receptors

Collaboration with the group of Prof. Haran from Weizmann

- Immune response of T-cells involves T-cell receptor (TCRs) molecules
- TCRs are clustered inside the Leukocyte microvilli
  - **STORM experiment with 30000 exposures**
- SPARCOM performs reliable recovery with **100 times shorter acquisition period**
  - Reconstruction of TCRs only at the focal plane!
  - May lead to live cell inspection of TCR arrangement

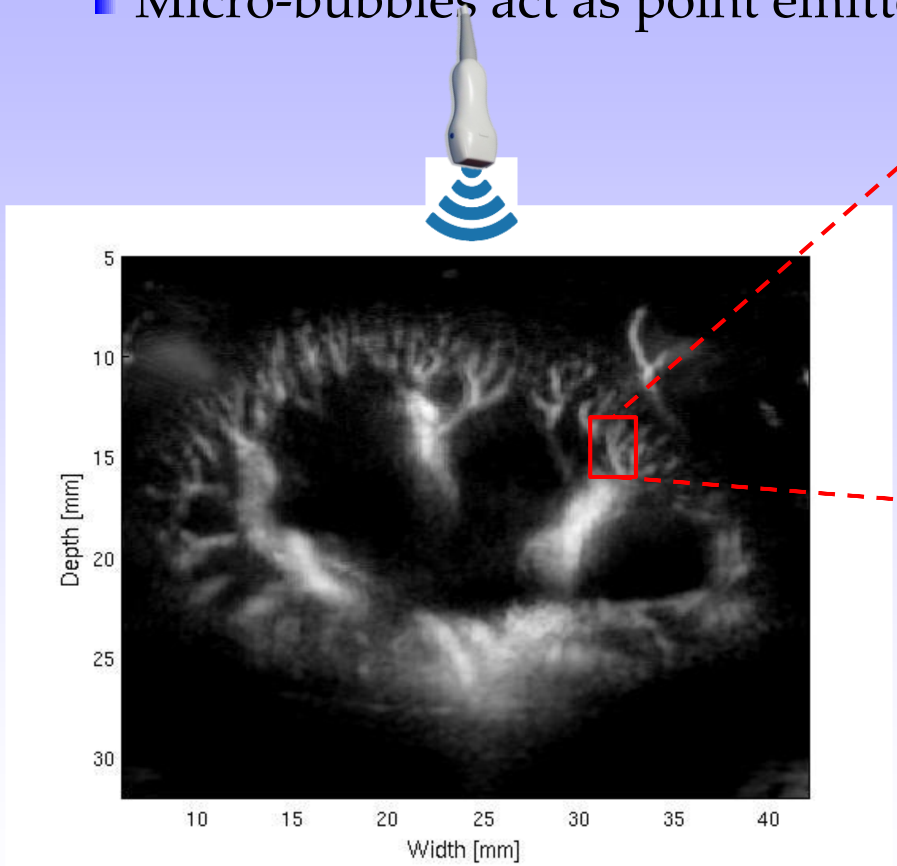




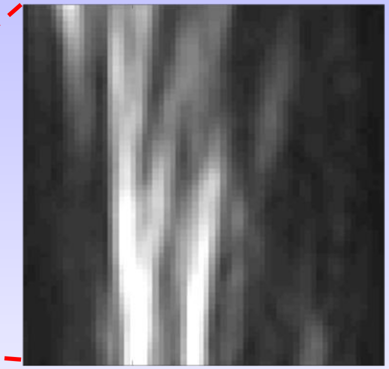
Super Resolution Contrast Enhanced Ultrasound

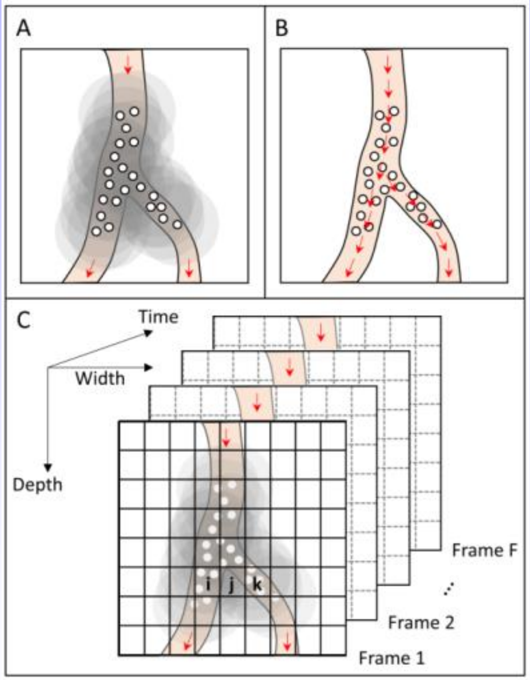
Bar Zion et. al 18

- Bolus injection of microbubbles into the blood stream
- Acquisition of consecutive frames to produce sub-wavelength image
- Micro-bubbles act as point emitters in the bloodstream

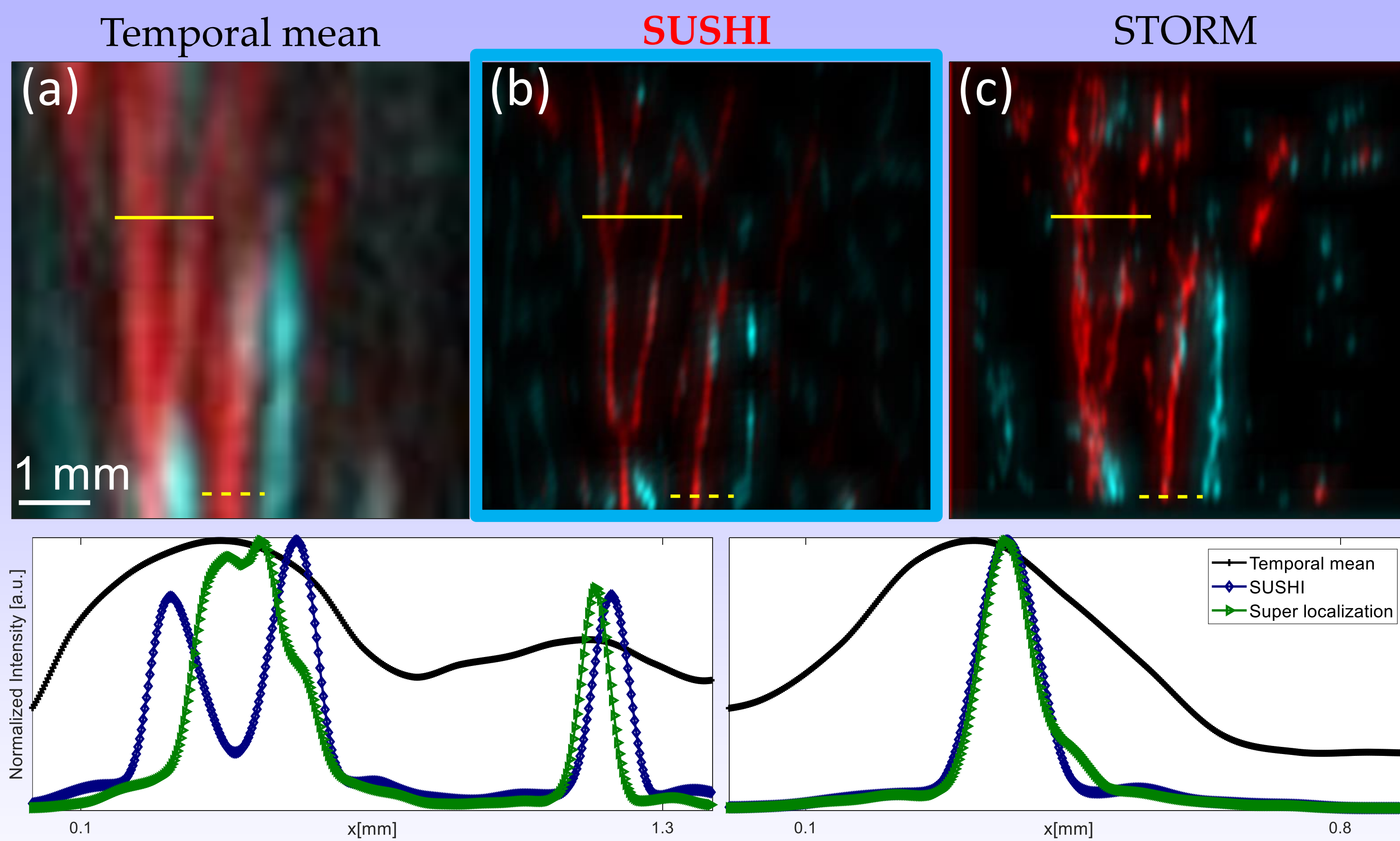


Temporal Mean





SUSHI: Sparsity-Based Ultrasound Super-resolution Hemodynamic Imaging



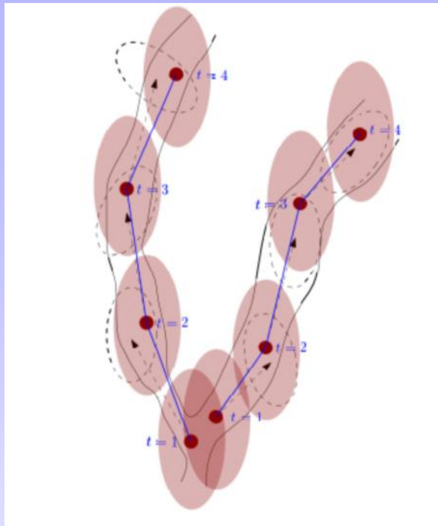
- Super-resolution imaging using CEUS in real-time
- Application: relapse detection & treatment monitoring in Crohn's disease
- Clinical evaluations with Dr. Anat Ilivitzki at Rambam

RAMBAM

Exploiting Flow Dynamics

- Contrast agents flow is structured: within blood vessels
- Exploit flow to improve sparse recovery

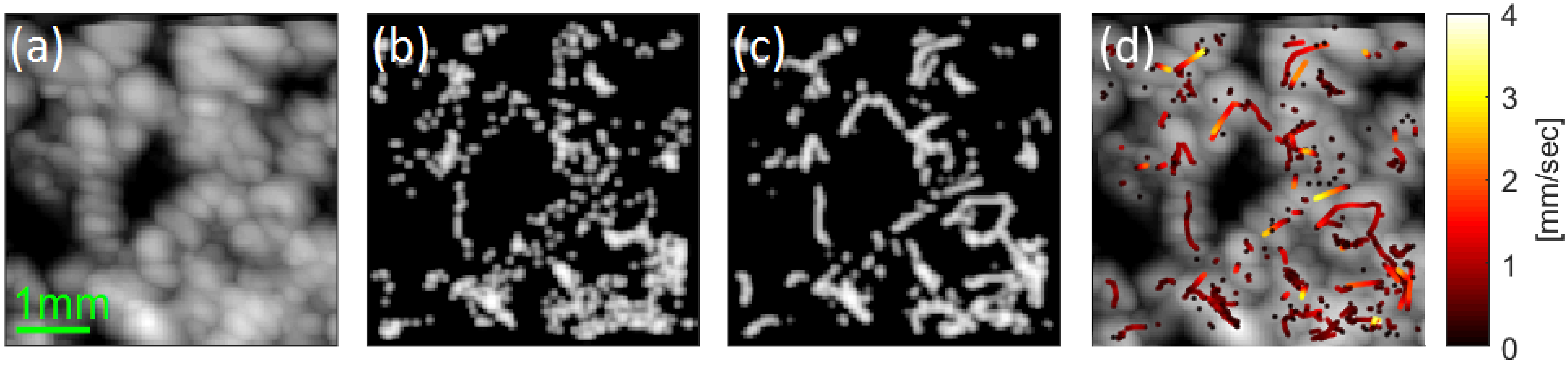
Solomon et. al 18



Method:

- Combine sparse recovery with on-line tracking
- Use current locations as weights in sparse recovery
- Tracking by optical flow and Kalman filtering
- Yields estimate of contrast agents velocities

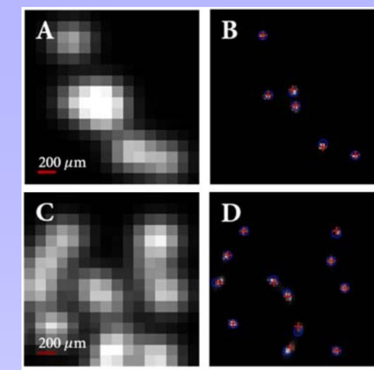
Diffraction limited | Frame-by-frame sparse recovery | Sparse recovery by exploiting flow | Velocities estimate



Super-resolution via Deep Learning

Van Sloun et. al. 2018

- Resolve overlapping UCAs via deep network scheme
  - Comparable performance to sparse recovery methods
  - Faster execution time
- Relies on the popular U-net architecture



- **Cost function:**

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

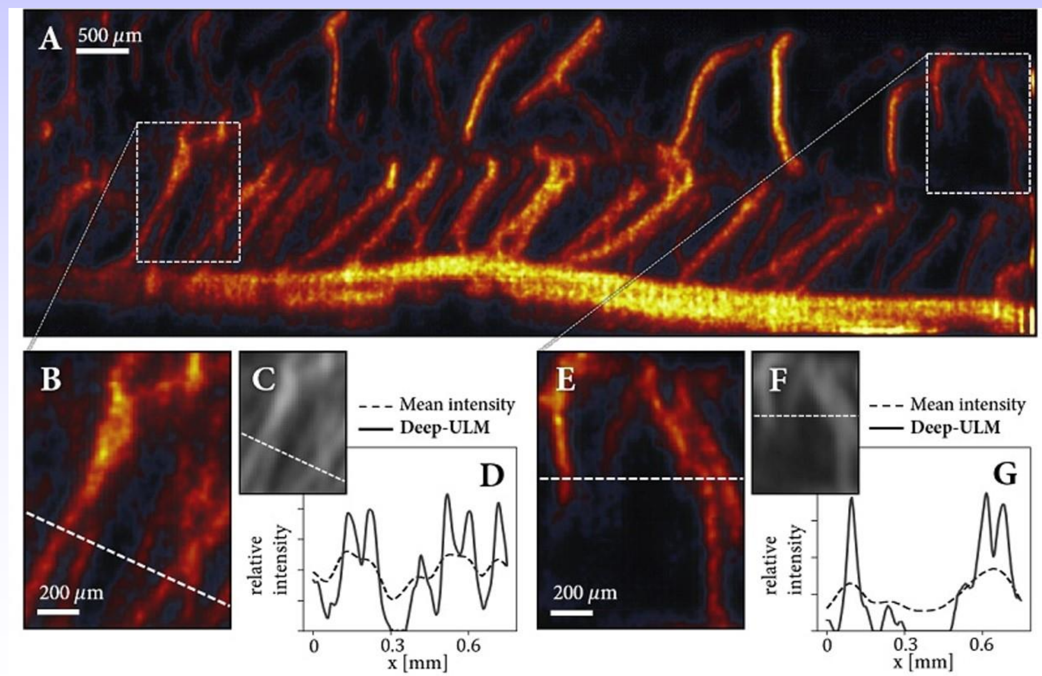
Network

Parameters

Super-resolved frame

Small convolution kernel

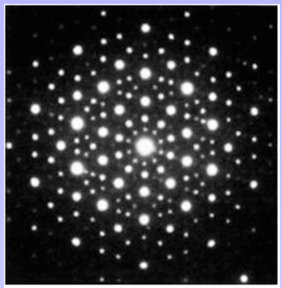
Super-resolution of rat spinal cord vasculature



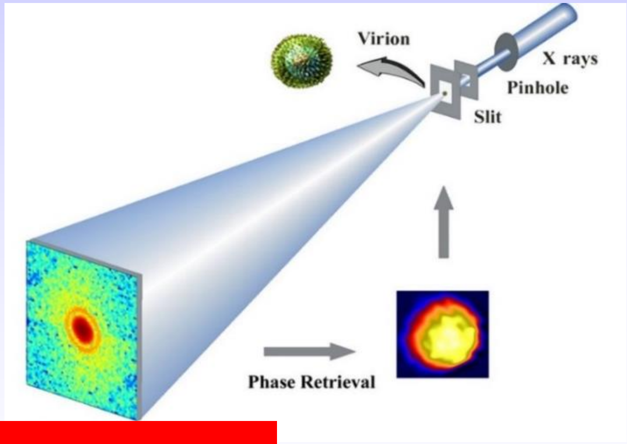
Phase Retrieval: Recover a signal from its Fourier magnitude

Collaboration with Profs. Moti Segev and Oren Cohen, Technion

$x[n] \rightarrow$ Fourier + Absolute value $\rightarrow y[k] = |X[k]|^2$



- Arises in many fields: crystallography (Patterson 35), astronomy (Fienup 82), optical imaging (Millane 90), and more
- Given an optical image illuminated by coherent light, in the far field we obtain the image's Fourier transform
- Optical devices measure the photon flux, which is proportional to the magnitude
- Phase retrieval can allow direct image recovery

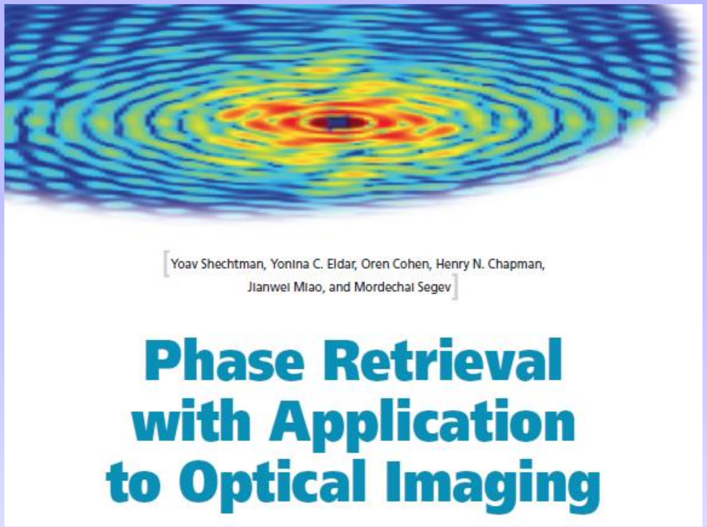


Using ideas of structure and optimization we can enable phase recovery

Reviews

Recent overview:

Y. Shechtman, Y. C. Eldar, O. Cohen,
H. N. Chapman, J. Miao, and M. Segev,
"Phase retrieval with application to optical imaging,"
SP magazine 2015



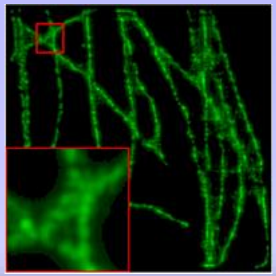
Book chapters:

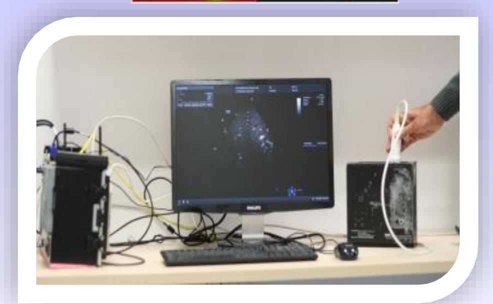
K. Jaganathan, Y. C. Eldar, and B. Hassibi,
"Phase Retrieval: An Overview of Recent Developments,"
In *Optical Compressive Imaging* edited by A. Stern

T. Bendory, R. Beinert and Y. C. Eldar, "Fourier Phase Retrieval: Uniqueness and Algorithms", In *Compressed Sensing and its Applications: MATHEON Workshop*

Conclusions

- Sub-Nyquist sampling of many classes of signals
- Reduce scanning time and increase resolution by exploiting structure
- Structure also aids in robust interpolation
- Super resolution in microscopy and ultrasound using structure in the correlation domain
- Portable ultrasound based on sub-Nyquist techniques
- In the context of optics allows recovery of sub-wavelength info from optical far field and recovery from loss of phase





Can substantially reduce scanning times, device size, and increase imaging performance by carefully exploiting structure in analog and digital domains!

Future Vision

Exploit structure and goal

Mathematical limits:
Sampling rates
Coding rates
Superresolution limits

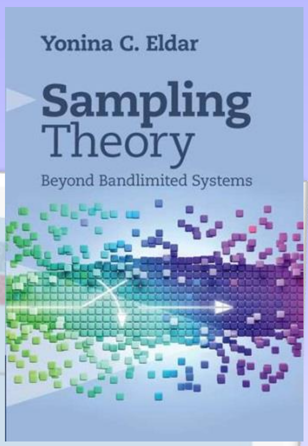
Engineering research:
Development of new samplers
Technological applications
that break existing barriers

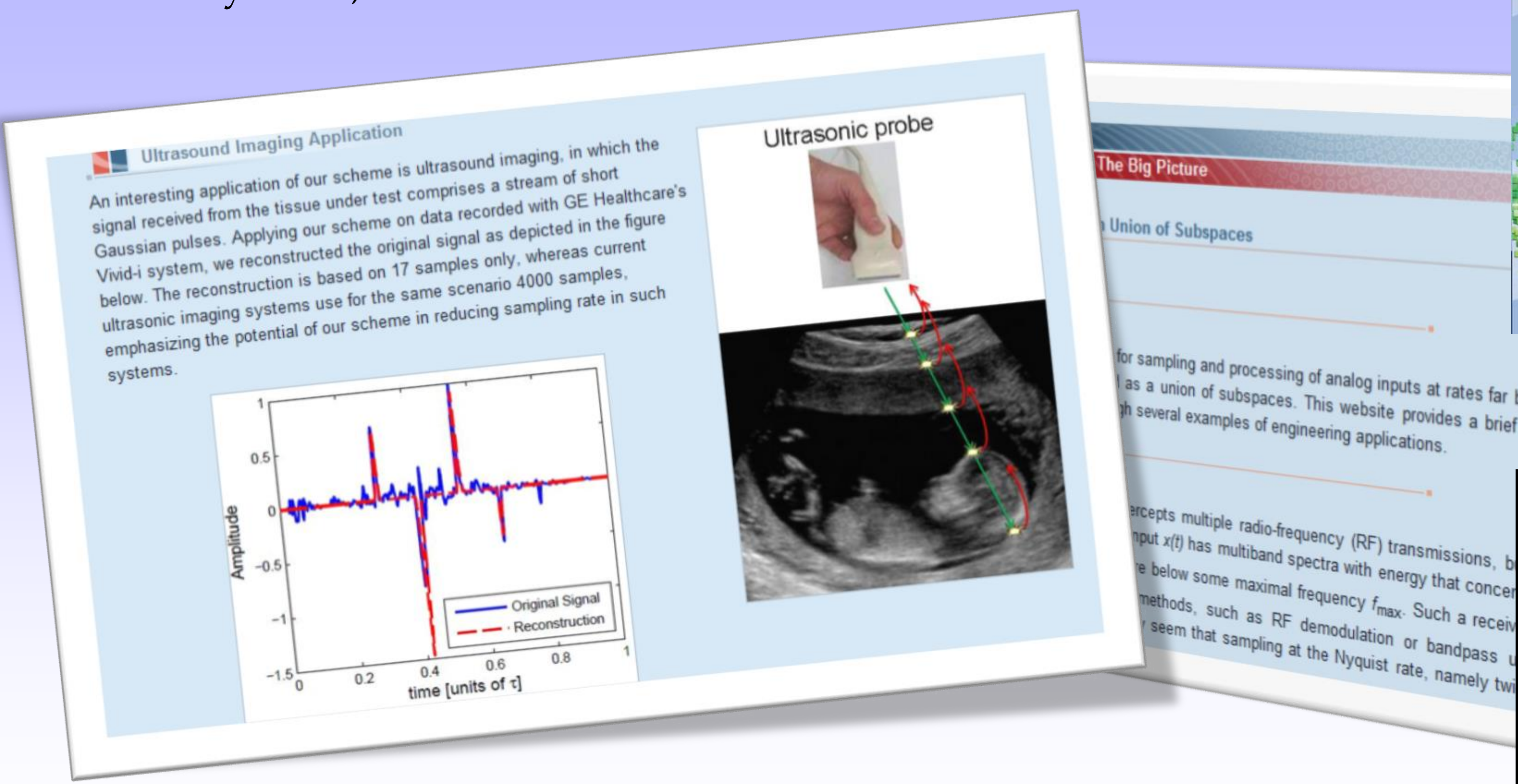
Scientific breakthroughs:
Thanks to the possibility of
seeing what we could
not see before ...

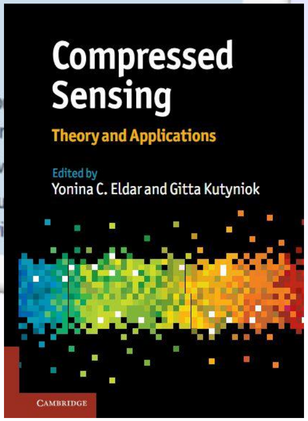
Xampling Website

webee.technion.ac.il/people/YoninaEldar/xampling_top.html

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







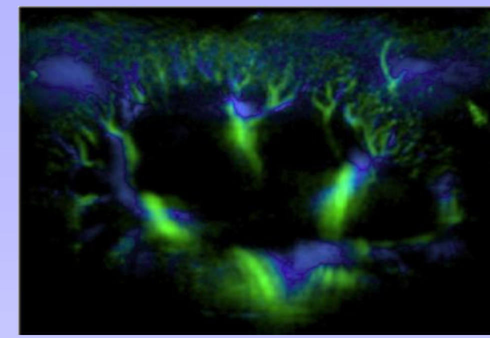
Y. C. Eldar and G. Kutyniok, "Compressed Sensing: Theory and Applications", Cambridge University Press, 2012

SAMPL Lab Website

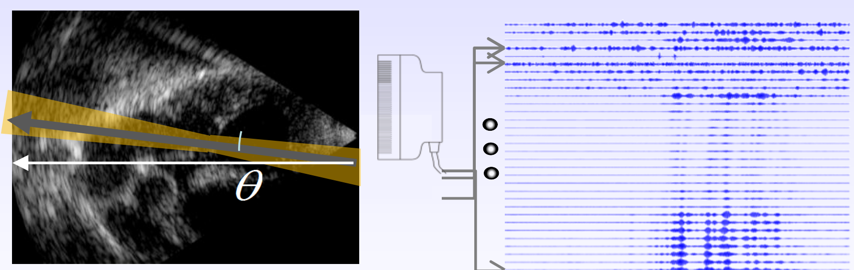
www.sampl.technion.ac.il

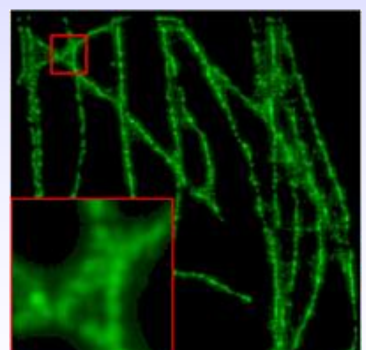
SAMPL Team

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



Thank You!





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