

Future of Spectral Use

Mind the Gap

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School of Electrical, Computer, and Energy Engineering



**President
of Big Little Sensors**



BIG · LITTLE · SENSOR

**President
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Integrated Circuits**



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Prof. Daniel W. Bliss

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- Professor in School of Electrical, Computer, and Energy Engineering
- Director of WISCA
- Published over 250 papers and articles
- Provided foundational contributions to
 - Multiple-input multiple-output radar
 - Adaptive MIMO communications
 - RF convergence (spectrum sharing, ISaC, ...)
 - Distributed-coherent systems
 - In-band full-duplex systems
 - Advanced positioning, navigation, and timing
- Spun out companies
 - President/CEO of Dash Tech Integrated Circuits, Inc. and Big Little Sensor Co.

Textbooks



IEEE Warren D. White Award for Excellence in Radar Engineering



Undergrad



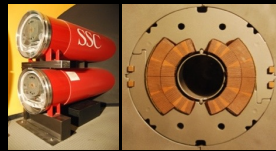
EE – 1989

Rocket Avionics



Early Work

Particle Accelerators

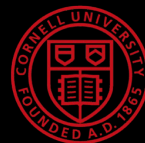


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Grad School



MS and PhD Physics,
1995 & 1997



Prior Position



1997-2012

Currently



Electrical
Engineering
2013-

Startups



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How Do We Get There?

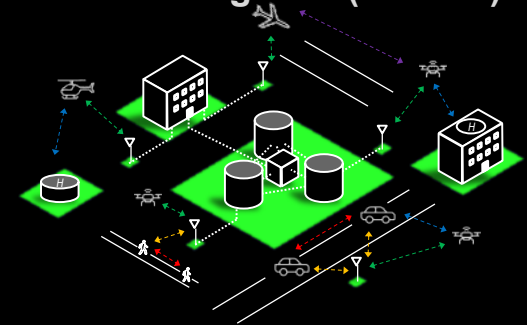
- **Review Goals and Implications of Heilmeier Questions**
- **Underlying Physics of Applications**
- **Explore New Enabling Technologies**
- **Explore Metrics of Performance**
- **Investigate Examples**



Future Wireless “Needs” ... OK, Desires

- Want faster, more flexible, more available communications
- Want new functionalities that we didn't know we wanted
 - Communications; sensing; positioning, navigation, and timing (PNT); environmental situational awareness; and ?
- Want lower cost, size, weight, and power

RF Convergence (or ISaC)



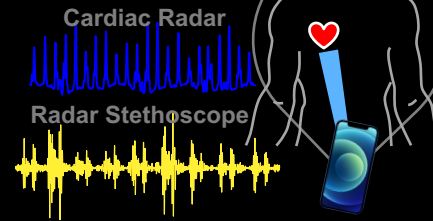
Next Generation Communications



Autonomous Vehicles



New Sensing Capabilities



Fully Immersive 3D Interactive Cat Café Simulations



Augmented Reality

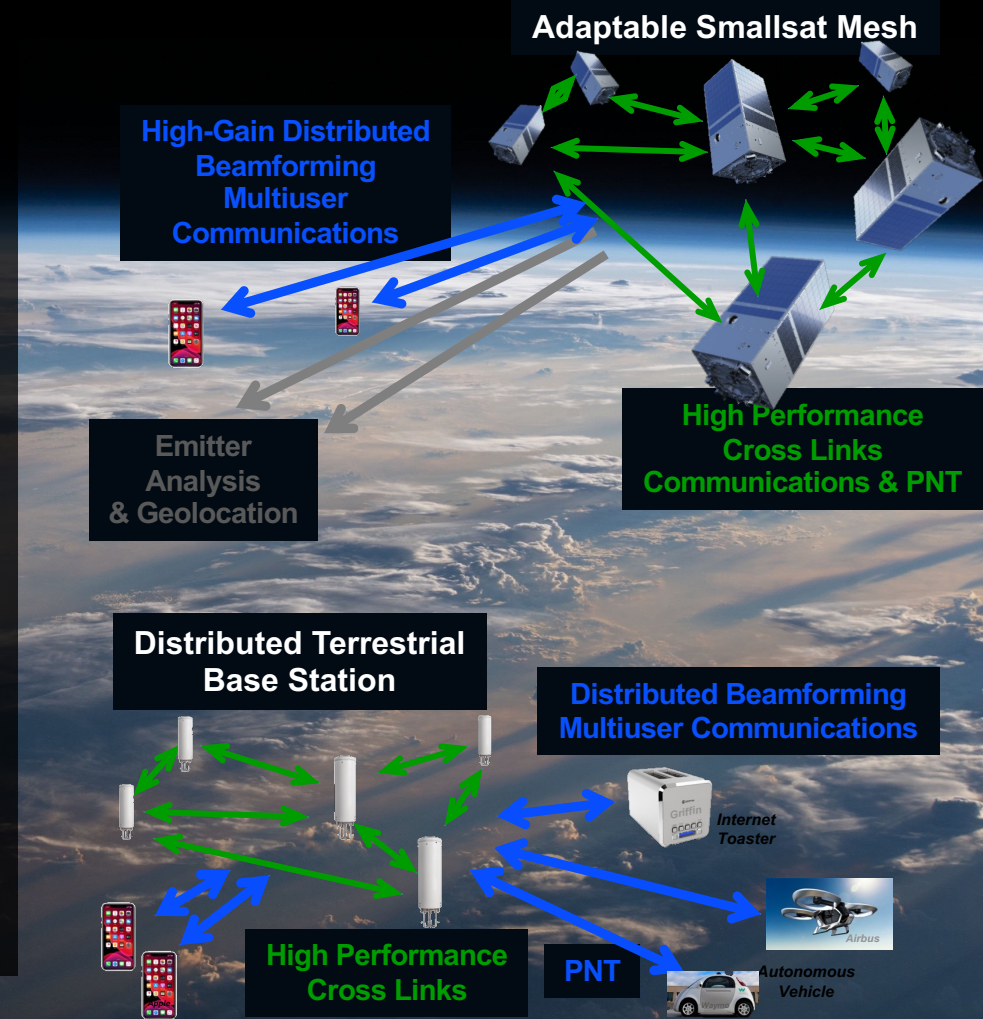


Who knows why,
but you know
it'll happen

Advanced Reconfigurable Systems

DC to Daylight

- Reinvent spectral employment by co-design of multi-function system
 - Provide transparent interface to spectrum
 - Higher data rate, better sensing, improved resilience
- Enable RF convergence
 - New functionalities
 - Multi-function systems
 - Communications, radar, PNT, etc...
- Enable flexible distributed carrier phase-coherent systems
 - Distributed wireless antenna arrays
- Integrate proliferated low C-SWaP space
- Develop advanced flexible systems
 - Bandwidth, power-scaling, dynamic range, ...
 - Flexible RF and optical
 - Flexible computations

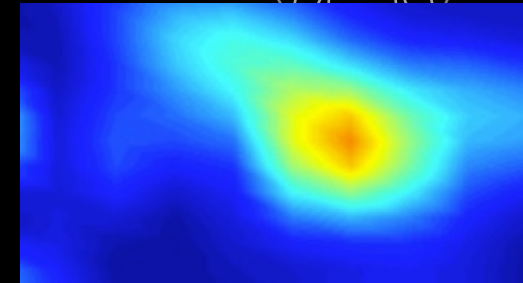


Physiological Radar

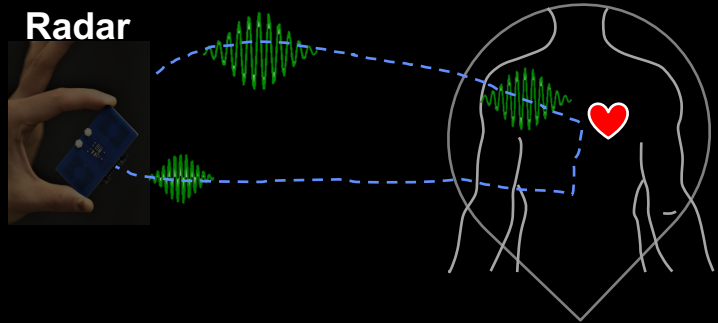


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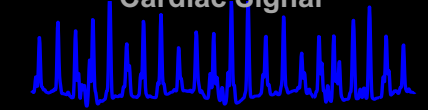
- **Extract hidden environmental information**
 - Extrasensory perception?
- **Use low-cost small-scale radar systems**
 - Could you use your phone as a tricorder?
- **Employs reasonably sophisticated algorithms**



Radar Cardiac Movie



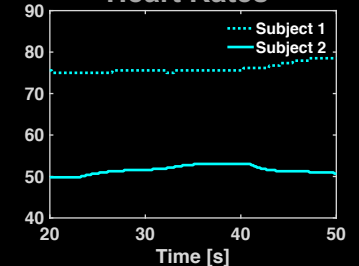
Radar-Estimated
Cardiac Signal



Radar-Estimated
Cardio-Acoustic Signal



Radar-Estimated
Heart Rates



Heilmeier Questions

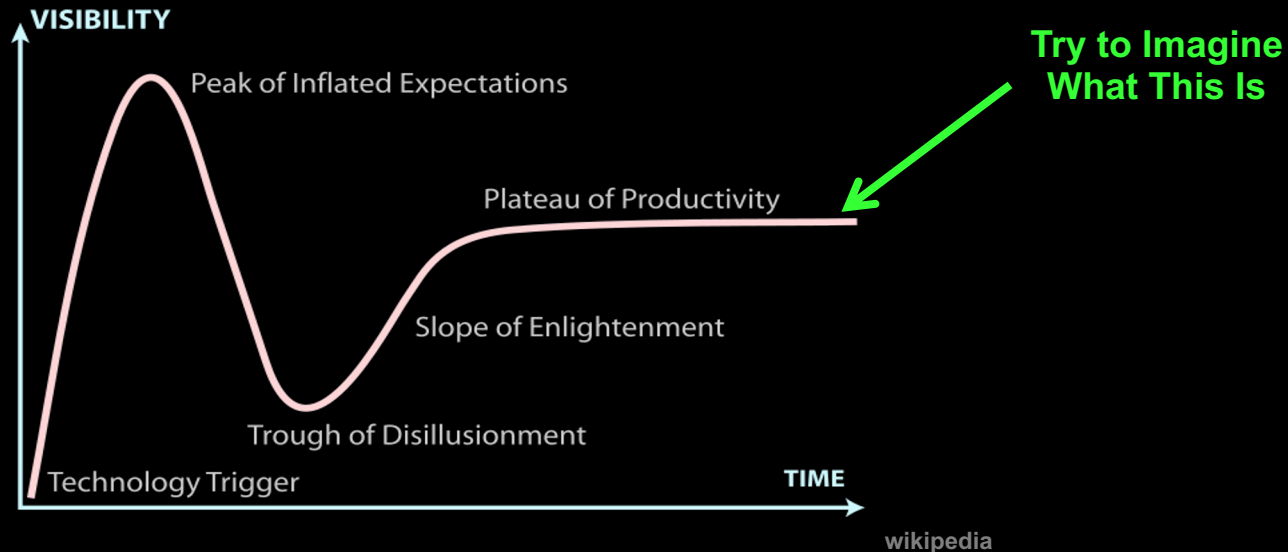
- **Defined key questions about technology/project development**
 - What are you trying to do?
 - How is it done today, and what are the limits of current practice?
 - What's new in your approach and why it will be successful?
 - Who cares? What difference will it make?
 - What are the risks and the payoffs?
 - How much will it cost?
 - How long will it take?
 - What are the midterm and final "exams" to check for success?
- **Answer these questions when consider your research**
- **Continuously consider to improve your research approach**



George Heilmeier
Director of DARPA, 1975-1977

Focus Our Research Questions

- **Here, focus on subset of Heilmeier questions**
 - How is it done today, and what are the limits of current practice?
 - What's new in your approach and why it will be successful?
 - Who cares? What difference will it make?
- **Avoid the sea of “good” ideas that contributed little**
- **Shoot for end of the Hype Curve**



How is it done today, and what are the limits of current practice?

- **Currently employ range or rigid single-function stove-piped systems**
 - Requires new signal and processing chain for each function
 - Limited ability to upgrade
 - Limited ability to adaptive to changing environments or system needs
 - Uses little outside information
- **Requires remote (cloud) processing for fusion and flexible processing**
 - Huge facility full of 19-inch racks of computers
 - Data movement is expensive and prone to security issues
 - Introduces significant latency to decision making
- **Ignores new functionalities enabled by integrated solutions**
 - More processing at edge

ETA Until Next Phone Upgrade?

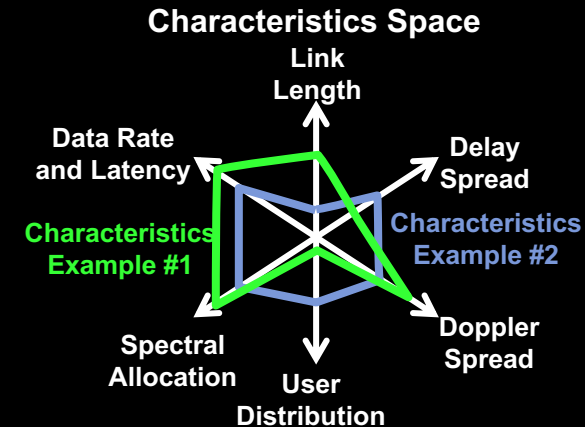
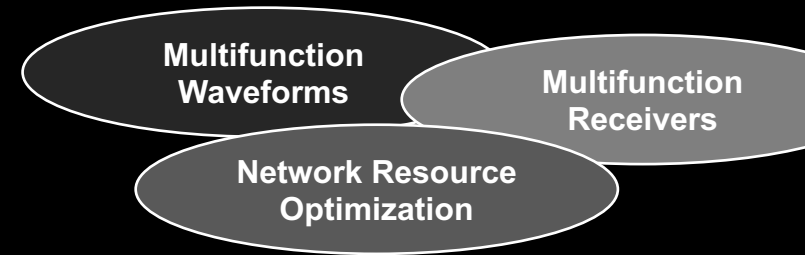
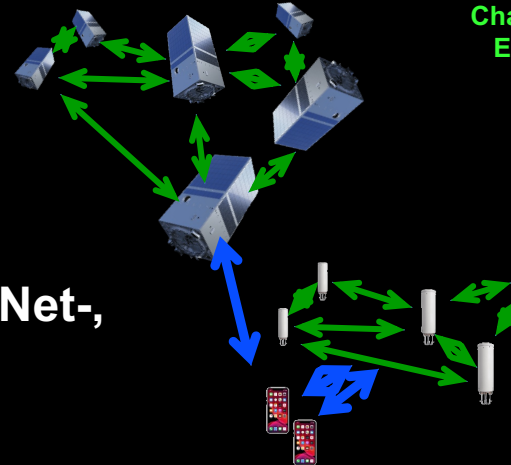


What Clouds Look Like



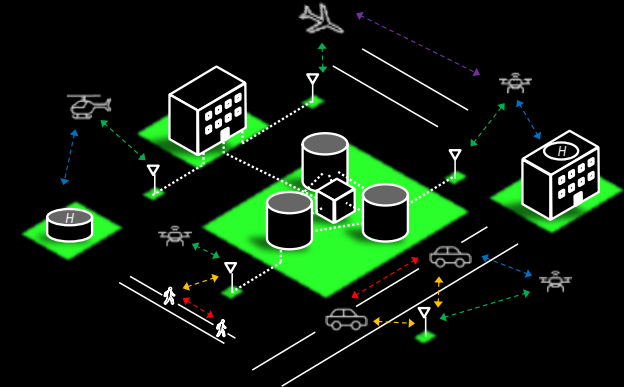
What's new in your approach and why it will be successful?

- Mix communications, radar, relative PNT, etc. into single system
- Extend functionality of system by using spectrum in multiple ways
- Fluidly adapt to needs of environment
- Leverage evolving technologies
 - Flexible frontends
 - Efficient, flexible processing
 - Distributed coherence
- Leverage heterogeneous connectivity: MANet-, terrestrial-, and satellite-based



Who Cares?

- **Applies to a wide range of users**
 - Enabling wide range of end-users', carriers', and spectrum managers needs
- **Reduce system cost - size, weight, and power (C-SWaP)**
 - Fluidly adjust functionality to system needs
- **Integration of functionality into single device**
 - Commercial “phones”
 - Smart homes and home security
 - Smart cities
 - Autonomous and semi-autonomous automotive applications
 - Uncrewed aircraft systems (UASs)
 - Flying cars (VTOL, EVTOL)



How Do We Get There?

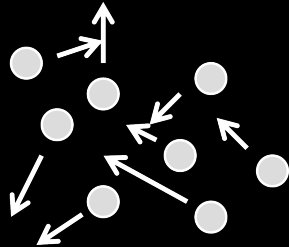
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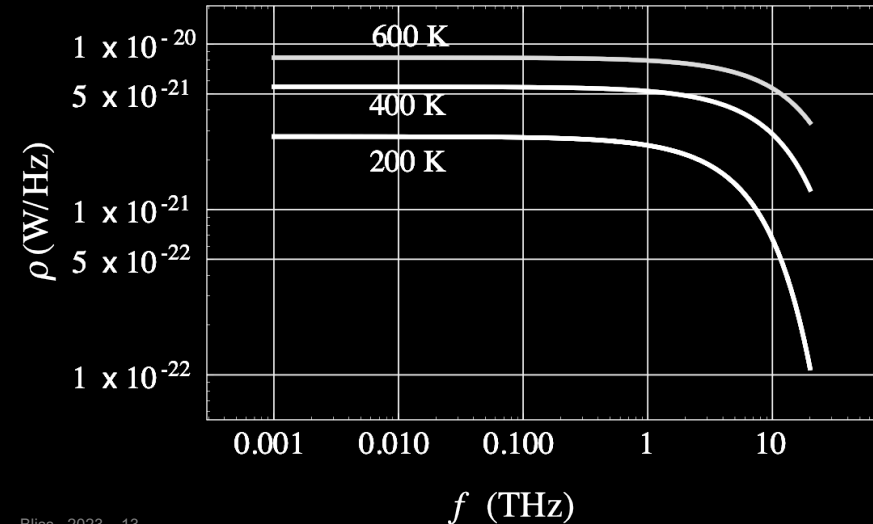
Noise

- Identify fundamental challenge to communications, detection, and estimation performance
 - Thermal noise, not interference

Large Number of Charged Particles



Noise Power Spectral Density



Fundamental Distribution of Noise

$$\rho_{\text{noise}}(f) = \frac{\overbrace{h f}^{\text{Planck Const.}}}{e^{\overbrace{k_B T}^{\text{Absolute Temperature}} - 1}}$$

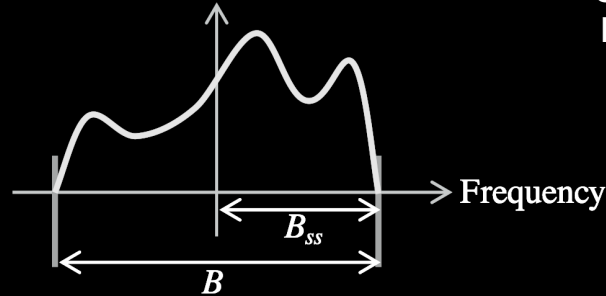
$$\approx \frac{h f}{1 + \frac{h f}{k_B T} - 1} = k_B \overbrace{T}^{\text{Boltzmann Const.}}; \quad \frac{h f}{k_B T} \ll 1$$

Typical Noise Power Approximation

$$P_{\text{noise}} = k_B T \underbrace{B}_{\text{Double-Sided Bandwidth}}$$

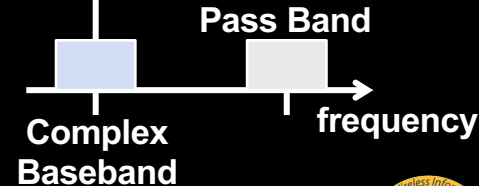
Double-Sided Bandwidth

Nyquist Rate Signal Spectrum



$$R_{Nyq} = 2 B_{ss} = B$$

Power Spectral Density



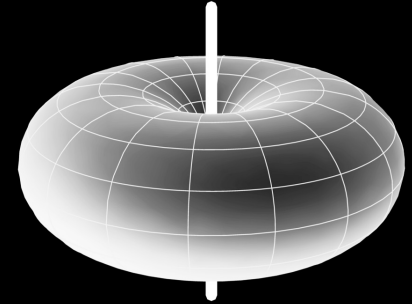
Antennas

- Convert voltages to magical waves wafting through the air
- Consider the dipole antenna



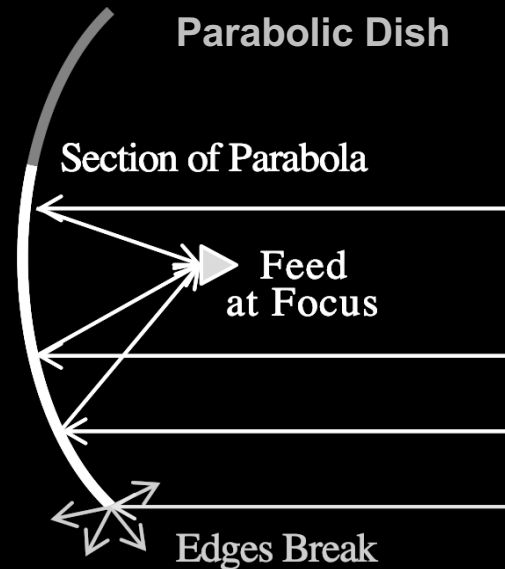
Small-Dipole Approximation
Radiation Pattern

$$P_{\text{rad}}(\phi, \theta) = \cos^2(\theta)$$



- Relate gain to effective area
 - Makes more sense for large antennas

$$\text{Gain } G = 4\pi \frac{\overbrace{A_{\text{eff}}}^{\text{Effective Area}}}{\underbrace{\lambda^2}_{\text{Wavelength}}}$$



Friis' and Phenomenological Equations

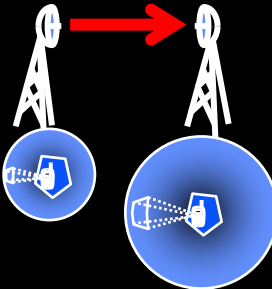
- Evaluate attenuation

- Power is reduced

$$\text{Received Signal } z(t) = \underbrace{\overbrace{a}^{\text{Attenuation}} s(t)}_{\text{Transmitted Signal}} + \underbrace{n(t)}_{\text{Noise}}$$

- Line-of-sight channel attenuation

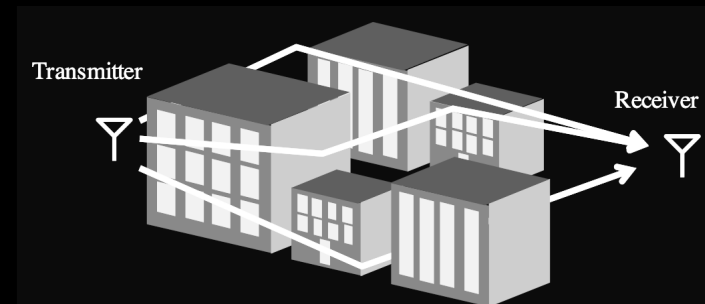
- Friis' Equation

$$\text{Attenuation In Power } \|a\|^2 = \frac{\overbrace{G_t G_r}^{\text{Transmit and Receive Gains}}}{\underbrace{(4\pi r/\lambda)^2}_{\substack{\text{Distance} \\ \text{Wavelength}}}}$$


- Complicated scattering

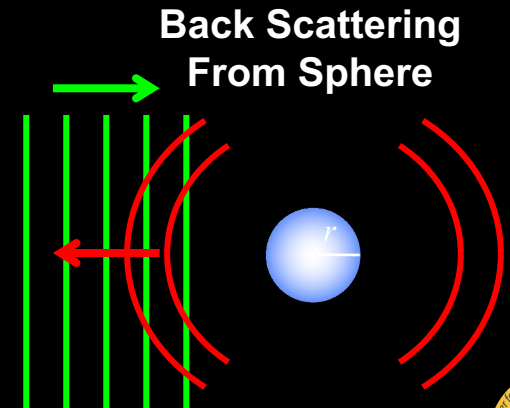
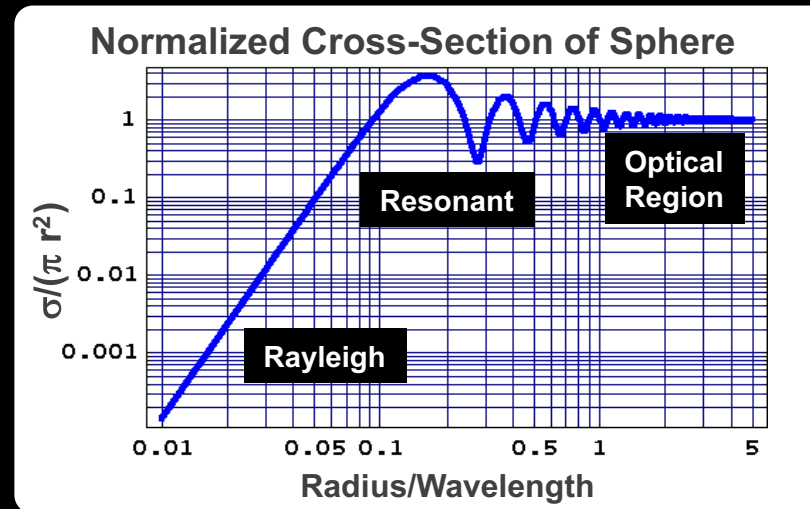
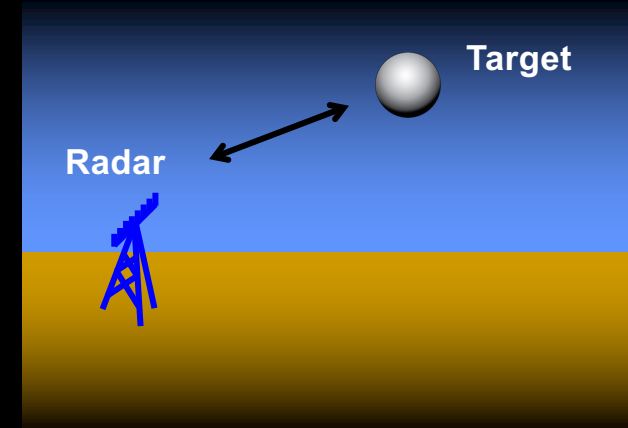
- Approximate model

$$\text{Attenuation In Power } \|a\|^2 = k \frac{1}{\underbrace{(r/\lambda)^\alpha}_{\substack{\text{Distance} \\ \text{Wavelength}}}}$$



Radar Return

- **Multiples effect of channel attenuation**
 - Transmitter to scatterer to receiver
 - $R_1^2 R_2^2$ loss for bistatic or R^4 loss monostatic
- **Consider cross section of sphere as reference target**
- **Three distinct regimes**
 - Rayleigh, $\sim r^6/\lambda^4$
 - Resonant
 - Optical



Return Power

- Consider constant illumination
 - Monostatic radar

- How much power is returned

- Power sent toward the target

$$P_t G_t$$

- Power flux at target

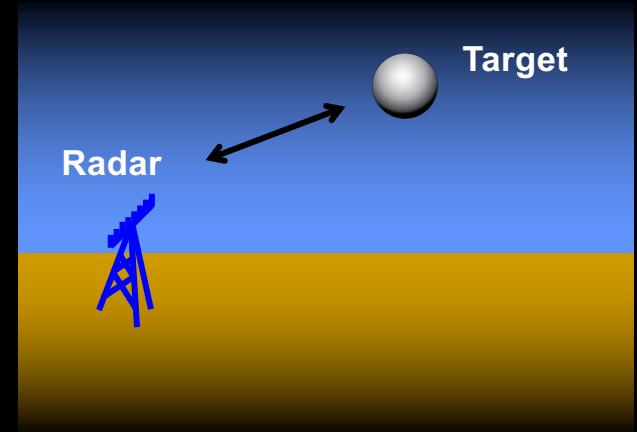
$$\frac{P_t G_t}{4\pi r^2}$$

- Target cross section (radiated back toward receiver)

$$\sigma \Rightarrow \frac{P_t G_t}{4\pi r^2} \sigma$$

- Power at receiver

$$\begin{aligned} P_r &= \frac{P_t G_t}{4\pi r^2} \sigma \frac{1}{4\pi r^2} A_{r,\text{eff}} = \frac{P_t G_t}{4\pi r^2} \sigma \frac{1}{4\pi r^2} \frac{G_r \lambda^2}{4\pi} \\ &= \frac{P_t G_t G_r \lambda^2 \sigma}{(4\pi)^3 r^4} \end{aligned}$$



Gain-Effective Area
Relationship

$$G = 4\pi \frac{A_{\text{eff}}}{\lambda^2}$$

Coherent Versus Incoherent Integration

Samples of Received Signal Plus Noise

- **Signal model**

- assume independent noise, \underline{n}

$$\underline{\mathbf{z}} = a \underline{\mathbf{s}} + \underline{\mathbf{n}}$$

Samples of Transmitted Signal

- **Consider energy at the output of matched filter**

$$E = \|\underline{\mathbf{z}} \underline{\mathbf{s}}^\dagger\|^2$$

- **Integrated SNR**

$$\text{ISNR} = \frac{E_s}{E_n} = \frac{\langle \|\underline{a} \underline{\mathbf{s}} \underline{\mathbf{s}}^\dagger\|^2 \rangle}{\langle \|\underline{\mathbf{n}} \underline{\mathbf{s}}^\dagger\|^2 \rangle}$$

Expected Value

Time-Bandwidth Product

- **Coherent integration of signal**

$$E_s = \langle \|\underline{a} \underline{\mathbf{s}} \underline{\mathbf{s}}^\dagger\|^2 \rangle = P_r n_s^2 = P_r (TB)^2$$

- **Incoherent integration of noise**

$$E_n = \langle \|\underline{\mathbf{n}} \underline{\mathbf{s}}^\dagger\|^2 \rangle = P_n n_s = P_n (TB)$$

Return SNR

- Received target power

$$P_r = \frac{P_t G_t G_r \lambda^2 \sigma}{(4\pi)^3 r^4}$$

- Thermal noise at receiver

$$P_n = k_B T_{\text{temp}} B f_n \quad \text{Noise Figure Versus Noise Factor}$$

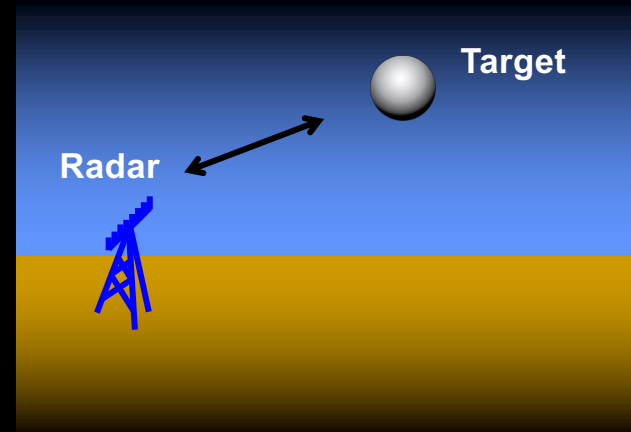
- SNR

$$\text{SNR} = \frac{P_r}{P_n} = \frac{P_t G_t G_r \lambda^2 \sigma}{(4\pi)^3 r^4 k_B T_{\text{temp}} B f_n}$$

- Integrated SNR

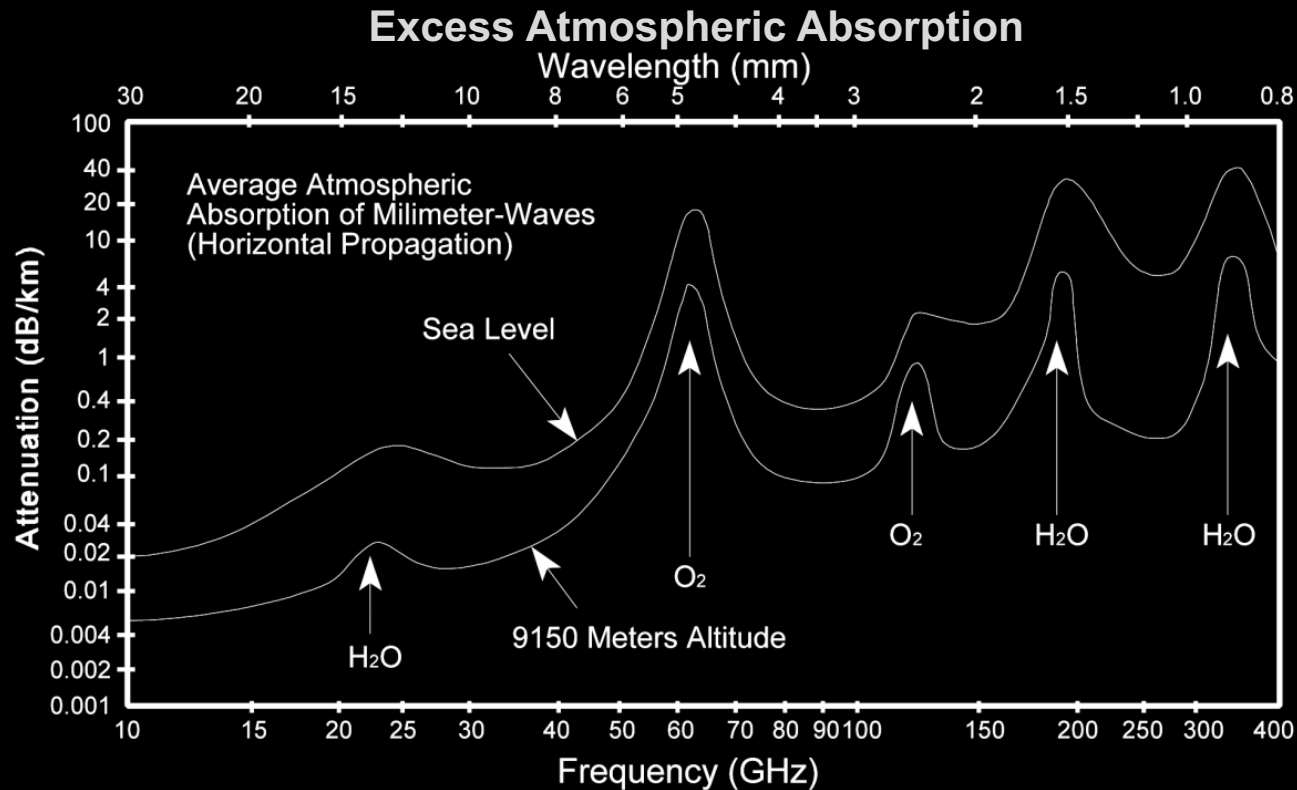
– Temporally and spectrally flat waveform

$$\text{ISNR} = T B \text{SNR} = T B \frac{P_t G_t G_r \lambda^2 \sigma}{(4\pi)^3 r^4 k_B T_{\text{temp}} B f_n}$$



“Line-of-Sight” Propagation

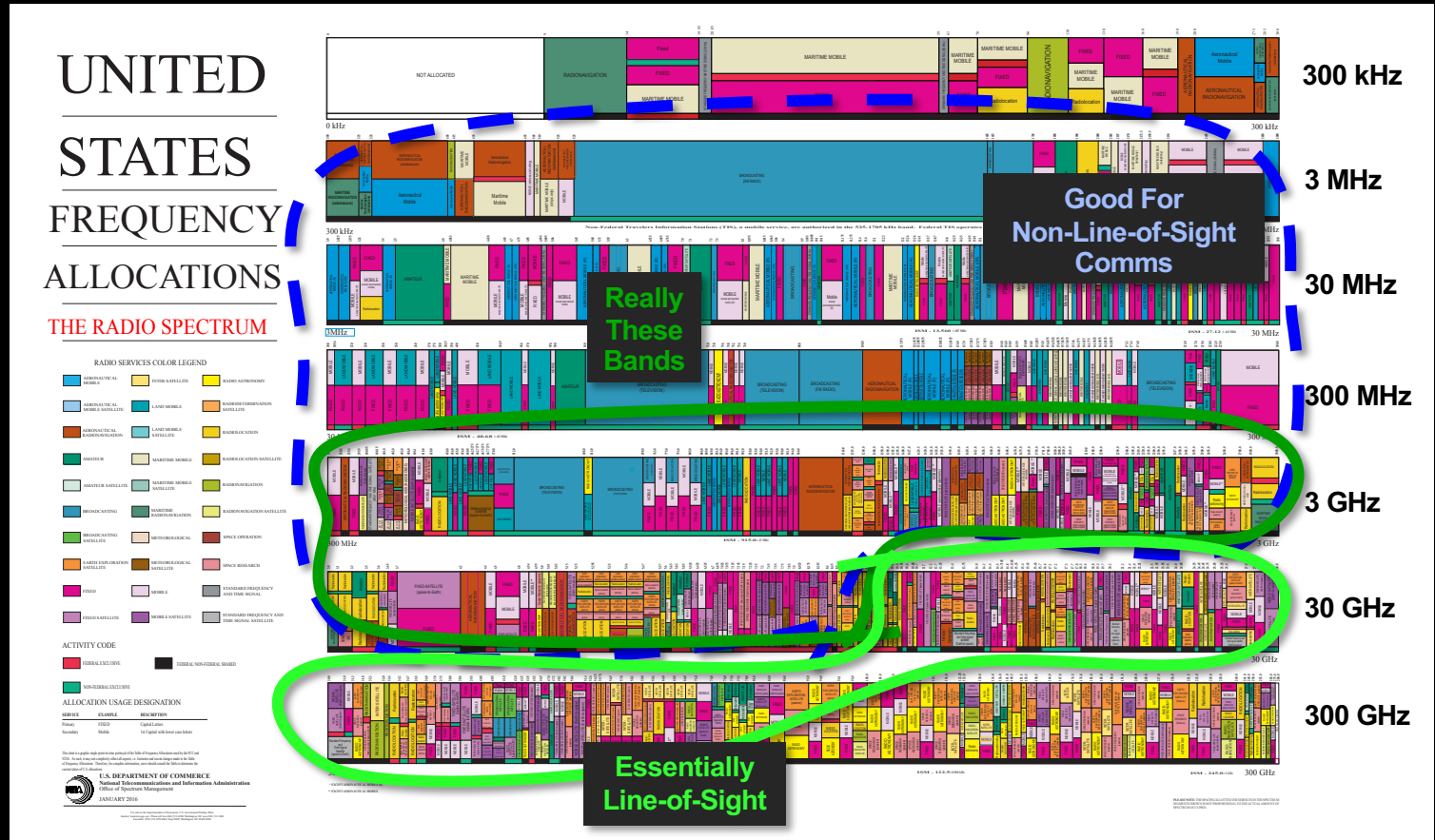
- Match spectrum to application
- Consider line-of-sight, range, bandwidth



Not a Lot of Unused Spectrum

Ok, None

- Find spectrum to operate your system
 - Well, that escalated quickly



Doppler Frequency Shift

Special Relativity

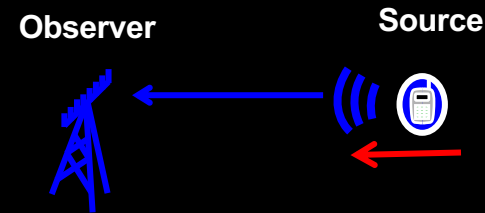
- Consider the basic physics
 - Invoke special relativity
 - Time dilation

$$\lambda = cT_s - vT_s; \quad \text{Galilean transformation}$$

$$T_s = \frac{\lambda}{c - v} = \frac{1}{(1 - \beta) f_s}; \quad \beta = \frac{v}{c}$$

$$T = \frac{T_s}{\gamma}, \quad \gamma = \frac{1}{\sqrt{1 - \beta^2}}; \quad \text{time dilation}$$

$$f = \frac{1}{T} = \gamma(1 - \beta) f_s = \frac{1 - \beta}{\sqrt{(1 - \beta)(1 + \beta)}} f_s$$
$$= \sqrt{\frac{1 - \beta}{1 + \beta}} f_s$$



- Do you need to worry about special relativity (1000 m/s > Mach 3)?

$$f = \left[1 - \beta + \frac{\beta^2}{2} + O(\beta^3) \right] f_s$$

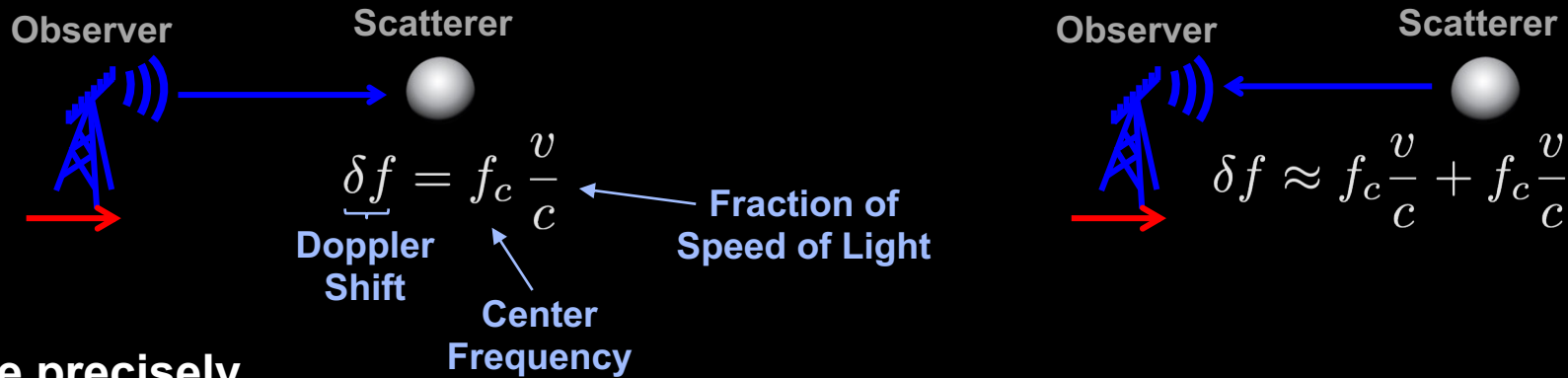
$$\beta = \frac{1000 \text{ m/s}}{3 \cdot 10^8 \text{ m/s}} \approx 3.3 \cdot 10^{-6}, \quad \frac{\beta^2}{2} = \frac{(1000 \text{ m/s})^2}{2(3 \cdot 10^8 \text{ m/s})^2} \approx 5.5 \cdot 10^{-12}$$

Sufficiently Accurate
Approximation

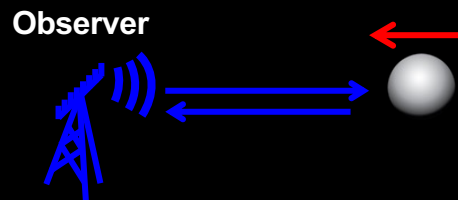
$$\Delta f_{\text{Doppler}} \approx \frac{v}{c} f_s$$

Radar Doppler Frequency

- Doppler frequency of monostatic radar is twice standard Doppler shift
- Easier to see if you think of a moving radar and static target



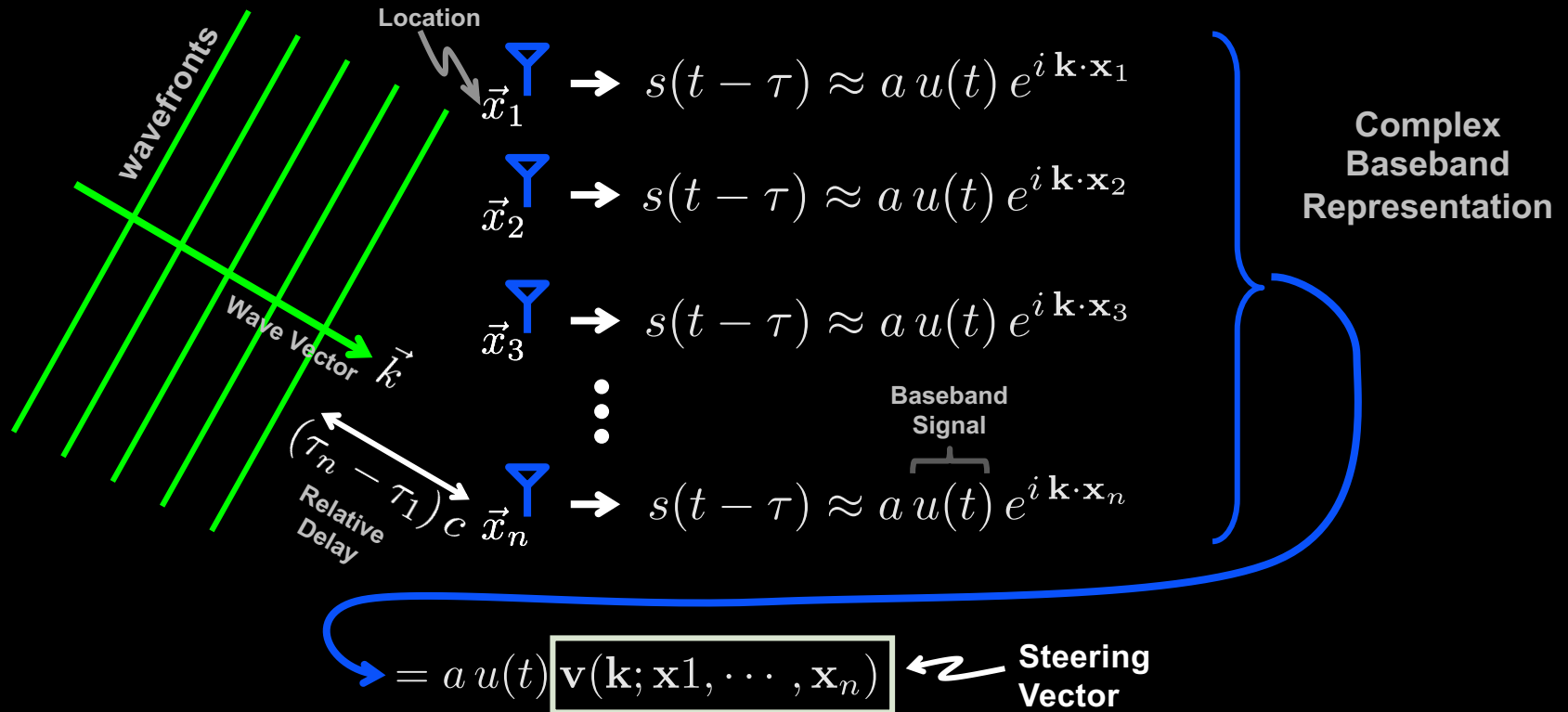
- More precisely
 - Assume short pulses
 - Assume monostatic
 - Assume v is small



Pulse Repetition Interval

Antenna Arrays

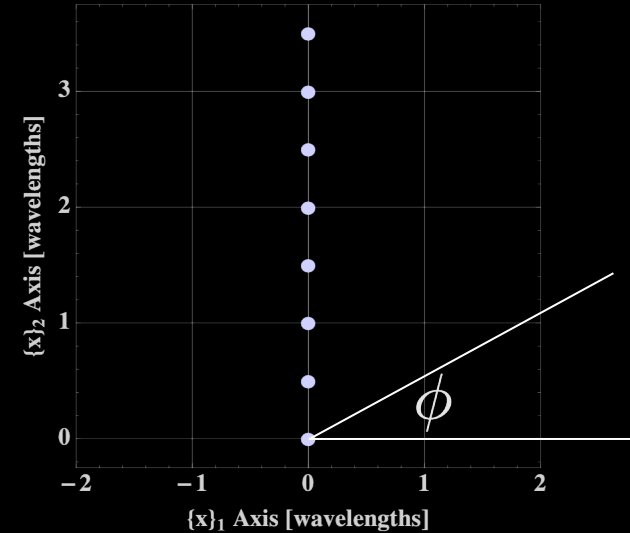
- Phase multiple antenna elements to control direction of transmitted or received power
- Narrowband model - can't resolve antennas, $B \ll \frac{c}{\|\mathbf{x}_1 - \mathbf{x}_n\|}$



Angle-of-Arrival Estimation

- Determine angle to source based upon observed phase on antennas
 - Lots of pseudo-spectrum techniques
 - Often associated with maximizing inner product between observation and model: $\vec{v}^\dagger \vec{z}$
- Consider simple spatial model
 - Array response “steering” vector

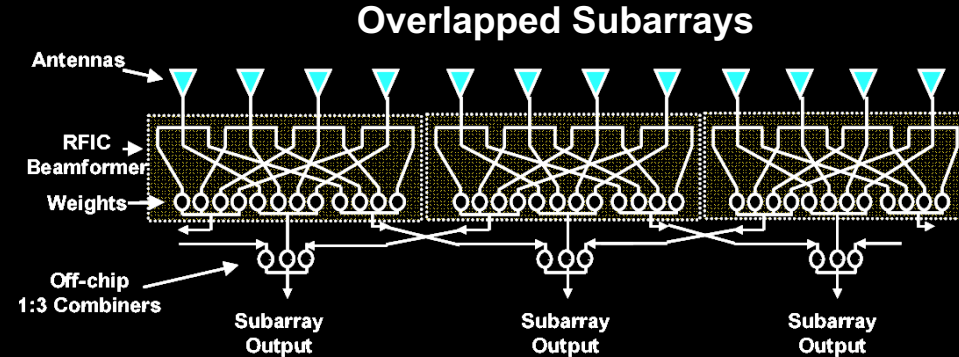
$$\vec{v}(\vec{k}; \vec{x}_1, \dots, \vec{x}_n) = \begin{pmatrix} e^{i \vec{k} \cdot \vec{x}_1} \\ e^{i \vec{k} \cdot \vec{x}_2} \\ \vdots \\ e^{i \vec{k} \cdot \vec{x}_n} \end{pmatrix} = \begin{pmatrix} e^{i \|\vec{k}\| \sin(\phi) 0 \lambda/2} \\ e^{i \|\vec{k}\| \sin(\phi) 1 \lambda/2} \\ \vdots \\ e^{i \|\vec{k}\| \sin(\phi) (n-1) \lambda/2} \end{pmatrix} = \begin{pmatrix} e^{i \pi \sin(\phi) 0} \\ e^{i \pi \sin(\phi) 1} \\ \vdots \\ e^{i \pi \sin(\phi) (n-1)} \end{pmatrix}$$



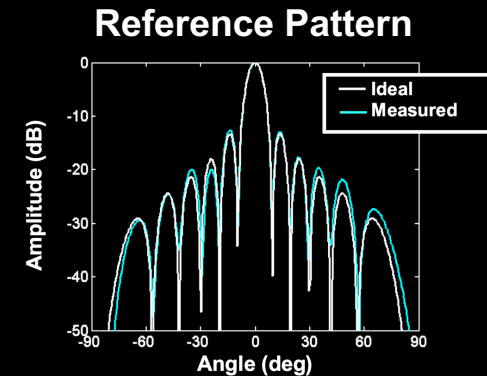
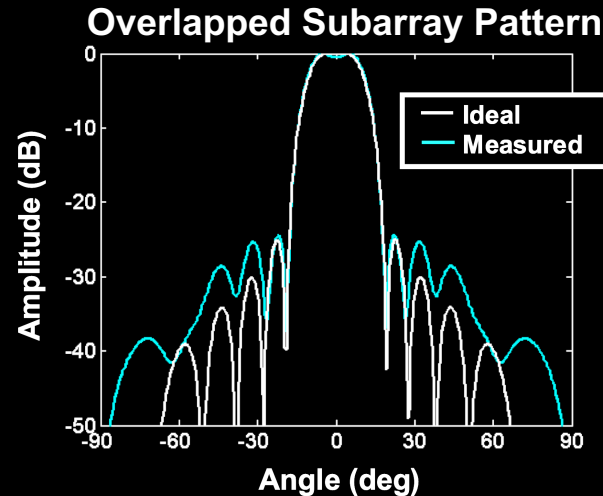
- Note: no one actually uses 1/2 wavelength space because antennas (or subarrays) have gain, so a larger spacing is employed

“Real” Antenna Arrays

- Reduce number of adapted phase centers by using subarrays
 - Hybrid approach
- Overlap subarrays to reduce sidelobes
- Employ true time-delay steering for large wideband scenarios
 - Space-Time beamforming
- Observe same pattern for transmit and receive because of reciprocity



S. Duffy, D. D. Santiago, J. Herd, “Design of overlapped subarrays using an RFIC beamformer”, IEEE Antennas and Propagation Society International Symposium, 2007



MuSiC

Multiple Signal Classification

- **Estimate angle of incoming signal**
 - Common approach is MuSiC
 - Inverse of norm squared of steering vector projected onto noise subspace

Pseudospectrum

$$P_{\text{music}}(\phi) = \frac{\mathbf{v}^\dagger(\phi) \mathbf{v}(\phi)}{\mathbf{v}^\dagger(\phi) \mathbf{P}_{\text{noise}} \mathbf{v}(\phi)}$$

Projection Operator

$$\mathbf{P}_{\text{noise}} = \sum_{m \in \mathcal{S}_{\text{noise}}} \mathbf{e}_m \mathbf{e}_m^\dagger$$

- **Decompose covariance matrix into eigen signal and noise subspaces**

$$\mathbf{R} = \underbrace{\sum_{m=1}^{n_{\text{noise}}} \lambda_m \mathbf{e}_m \mathbf{e}_m^\dagger}_{\text{noise}} + \underbrace{\sum_{m=n_{\text{noise}}+1}^{n_r} \lambda_m \mathbf{e}_m \mathbf{e}_m^\dagger}_{\text{signal}}$$

$$n_{\text{noise}} = \max\{m : \lambda_m \leq \text{threshold}\}$$

Noise Projection Operator

$$\left\{ \mathbf{P} = \sum_{m \in \text{noise}} \mathbf{e}_m \mathbf{e}_m^\dagger \right.$$

- **Model signal as ideal array response**

$$\mathbf{P}_{\text{signal}} = \frac{\mathbf{v}_0 \mathbf{v}_0^\dagger}{\mathbf{v}_0^\dagger \mathbf{v}_0} \quad \mathbf{P}_{\text{noise}} = \mathbf{I} - \mathbf{v}_0 (\mathbf{v}_0^\dagger \mathbf{v}_0)^{-1} \mathbf{v}_0^\dagger$$

True

Steering Vector

– Music pseudospectrum

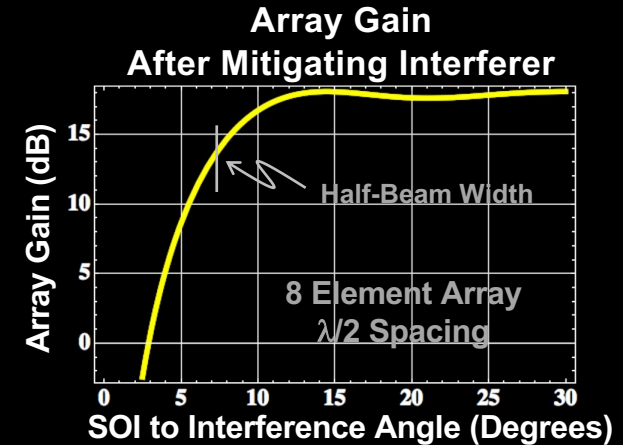
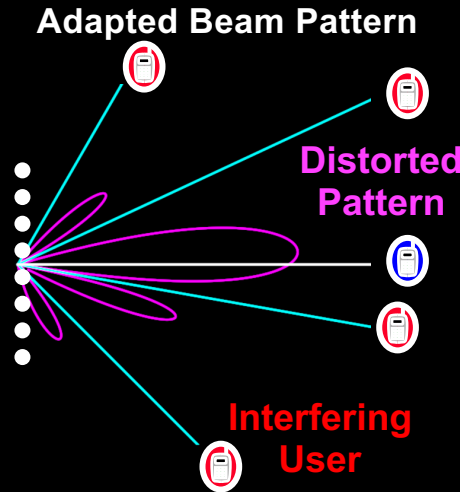
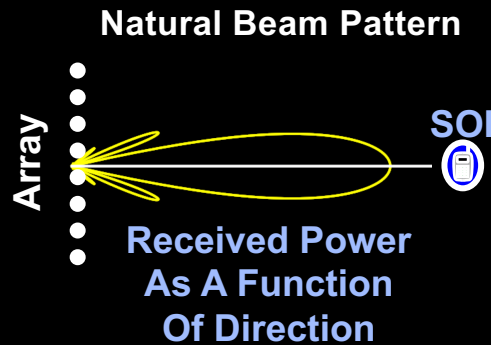
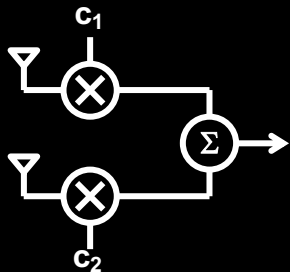
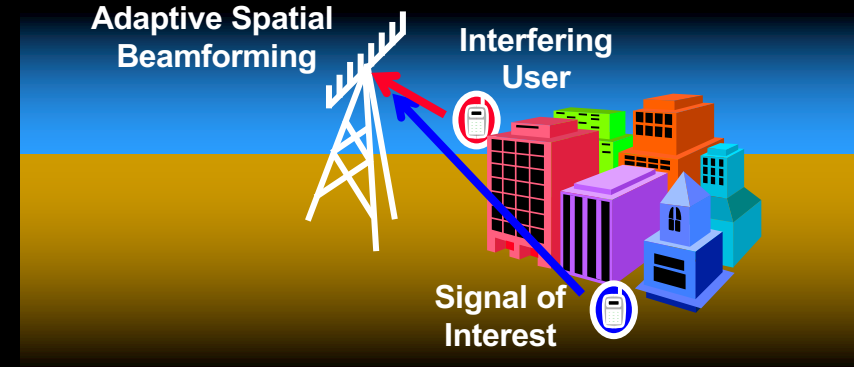
$$\begin{aligned} P_{\text{music}}(\phi) &= \frac{\mathbf{v}^\dagger(\phi) \mathbf{v}(\phi)}{\mathbf{v}^\dagger(\phi) \mathbf{P}_{\text{noise}} \mathbf{v}(\phi)} \\ &= \frac{\mathbf{v}^\dagger(\phi) \mathbf{v}(\phi)}{\mathbf{v}^\dagger(\phi) [\mathbf{I} - \mathbf{v}_0 (\mathbf{v}_0^\dagger \mathbf{v}_0)^{-1} \mathbf{v}_0^\dagger] \mathbf{v}(\phi)} \\ &= \frac{1}{\left[1 - \left\| \frac{\mathbf{v}^\dagger(\phi) \mathbf{v}_0}{n} \right\|^2 \right]} \end{aligned}$$

$$1 \leq P_{\text{music}}(\phi) \leq \infty$$

Adaptive Antenna Array Processing

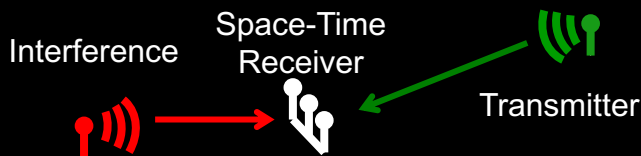
Spatial Interference Cancellation

- Focus on user of interest while nulling interference from other users
- Adapt antenna array beam pattern
 - Beam received signal at each antenna against others
 - Beam pattern adapted for each user simultaneously

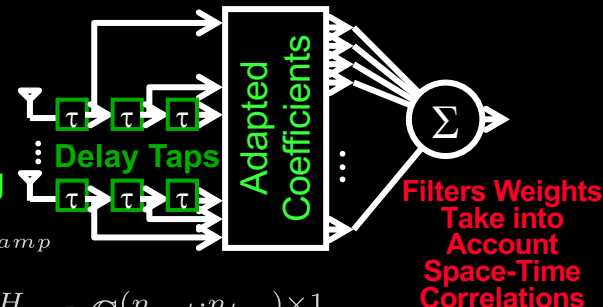


Radio Interference-Mitigation Approaches

- Enable higher RF density by mitigating interference
- Exploit space-delay correlations of interference sources to mitigate
 - Space-time adaptive processing (STAP)



Space-Time Adaptive Processing

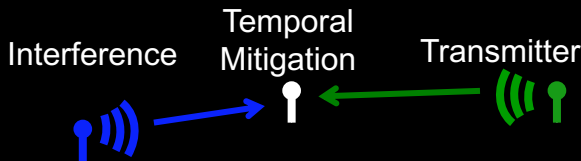


$$\mathbf{Z} \in \mathbb{C}^{(n_{ant} \cdot n_{tap}) \times n_{samp}}$$

$$\mathbf{w} = \underbrace{(\mathbf{Z}\mathbf{Z}^H)^{-1}}_{\hat{\mathbf{C}}} \underbrace{\mathbf{Z}\mathbf{s}_m^H}_{\hat{\mathbf{v}}_m} \in \mathbb{C}^{(n_{ant} \cdot n_{tap}) \times 1}$$

$$= \hat{\mathbf{C}}^{-1} \hat{\mathbf{v}}_m$$

- Exploit known temporal structure to mitigate
 - Temporal mitigation (estimation-subtraction)
 - Decodable interference

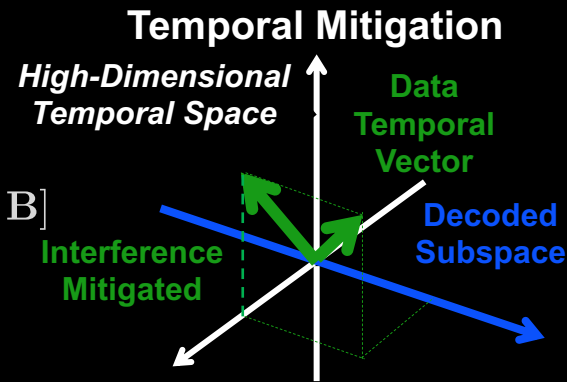


Projects onto Space Orthogonal to Known Interference Sequence

$$\tilde{\mathbf{z}} = \mathbf{z} [\mathbf{I} - \mathbf{B}^H (\mathbf{B}\mathbf{B}^H)^{-1} \mathbf{B}]$$

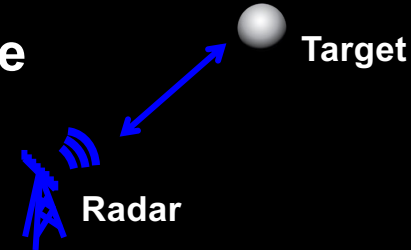
$$= \mathbf{z} - \hat{\mathbf{h}} * \mathbf{b}$$

$$\mathbf{B} = \begin{pmatrix} \mathbf{b}_{\tau_1} \\ \mathbf{b}_{\tau_2} \\ \vdots \end{pmatrix}$$

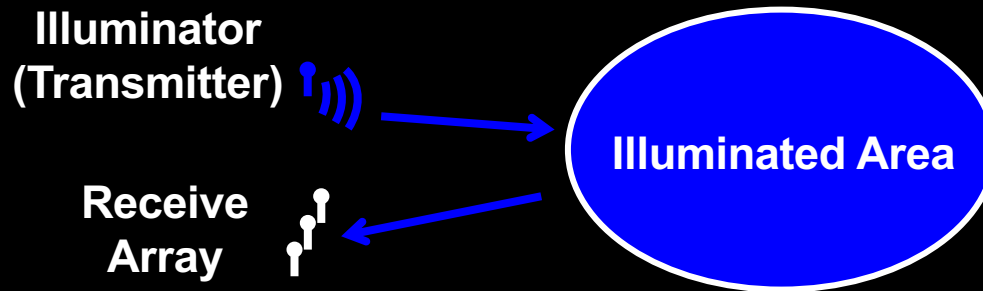


Radar Angle Estimation

- Estimate range, Doppler frequency, and angle
 - Focus on range and Doppler frequency, here



- Employ multiple phase centers
 - Angle information is encoded in the relative phase of the antennas
 - Narrowband assumption

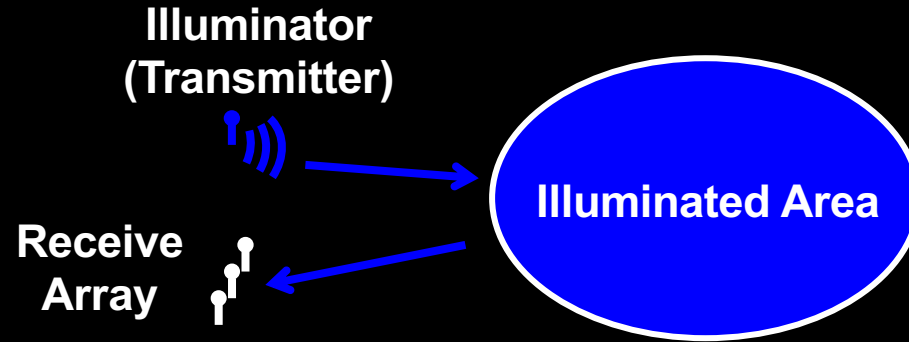


Simple Radar Received Signal Model

- **Illumination has pattern**

- Range dependent

- Propagation
- Antenna pattern



- **Angle information encoded in relative phase**

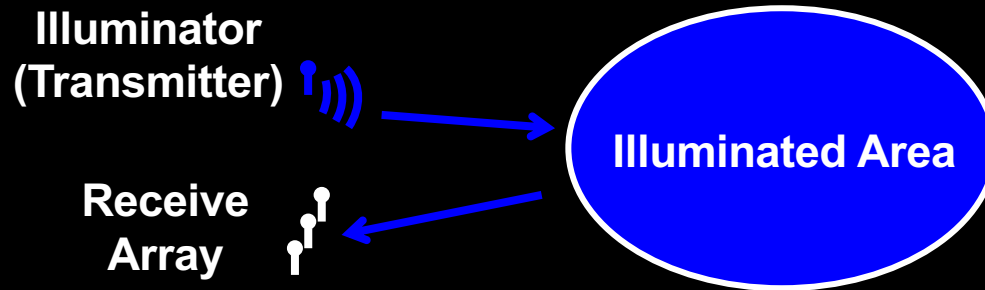
$$\mathbf{z}(t) = \sum_m a(\phi_m, r_m) \mathbf{v}(\phi_m) s(t - \tau_m) + \mathbf{n}(t)$$

$$\underbrace{\mathbf{v}(\phi_m)}_{\text{Steering Vector}} = \underbrace{\begin{pmatrix} e^{i \mathbf{k}_m \cdot \mathbf{x}_1} \\ e^{i \mathbf{k}_m \cdot \mathbf{x}_2} \\ \dots \\ e^{i \mathbf{k}_m \cdot \mathbf{x}_{n_r}} \end{pmatrix}}_{\text{Wave Vector}} = \begin{pmatrix} e^{i \frac{2\pi}{\lambda} \sin \phi_m x_1} \\ e^{i \frac{2\pi}{\lambda} \sin \phi_m x_2} \\ \dots \\ e^{i \frac{2\pi}{\lambda} \sin \phi_m x_{n_r}} \end{pmatrix} \underbrace{\phi_m}_{\text{Physical Angle}}$$

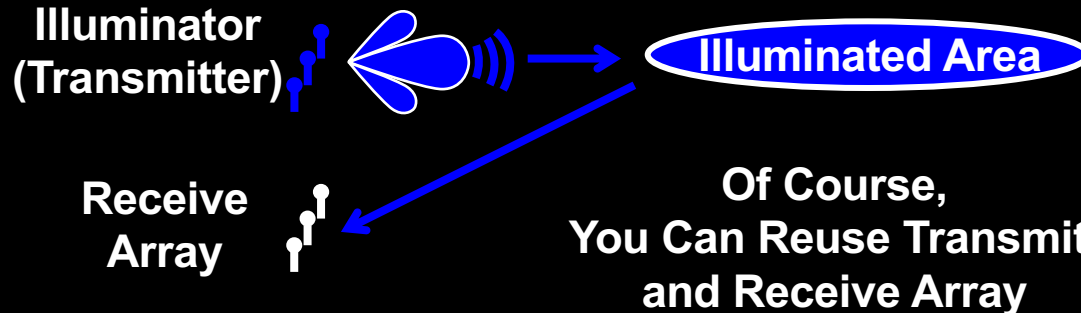
Considering Simple Linear Array

Radar Transmit Pattern

- Illuminate from single element

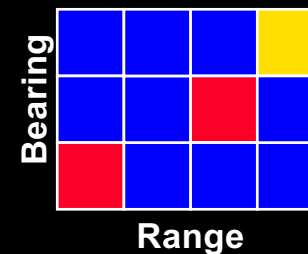
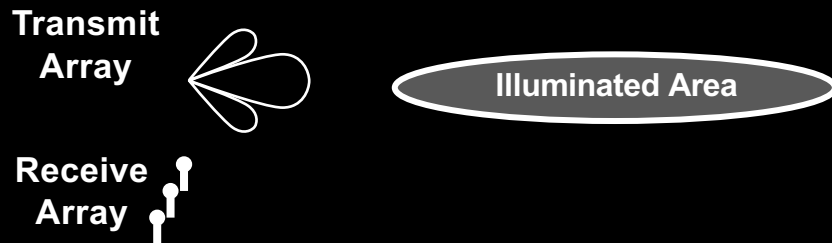


- Illuminate from beamformer

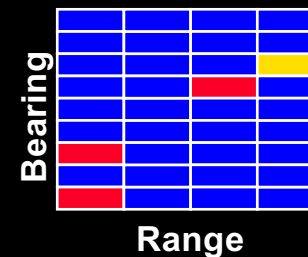
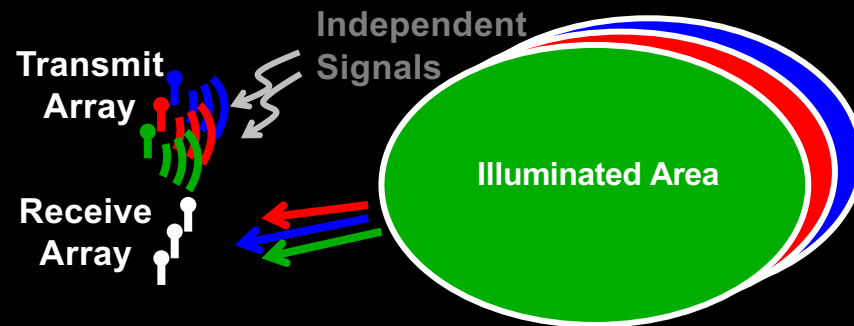


MIMO versus Traditional Coherent Radar

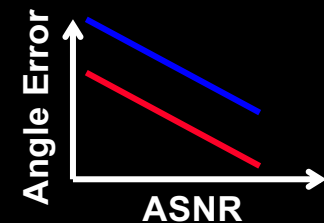
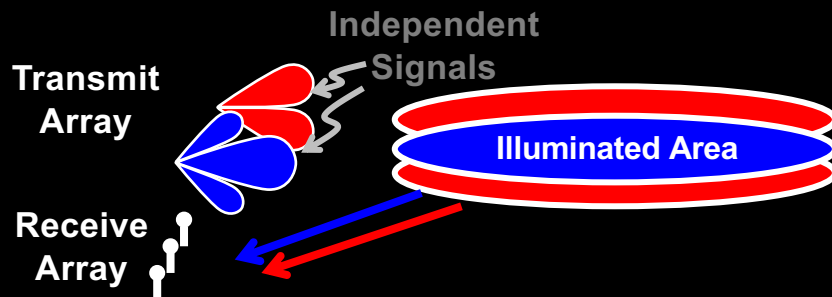
Traditional Radar



MIMO Radar

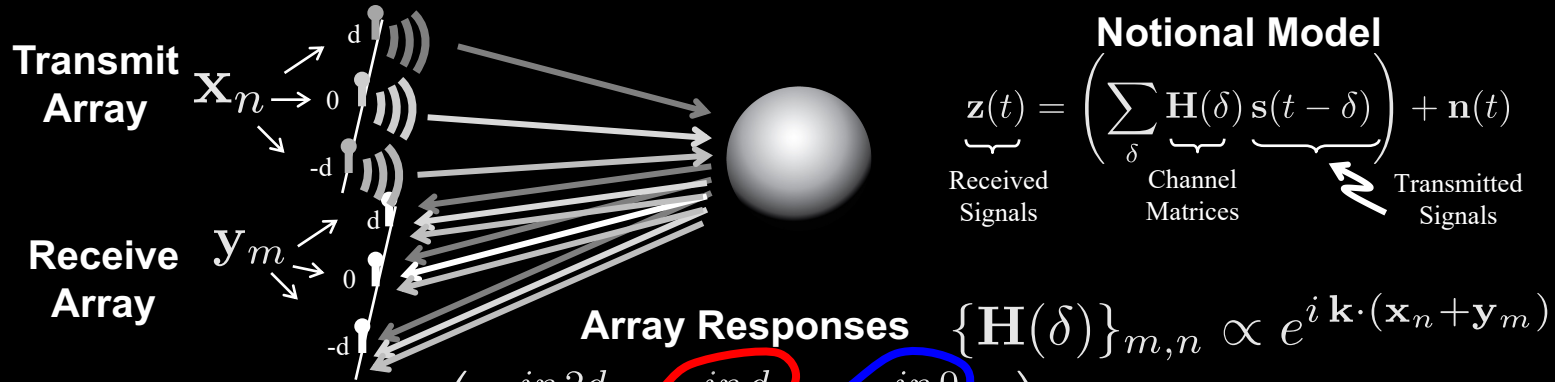


Multi-Beam MIMO Radar

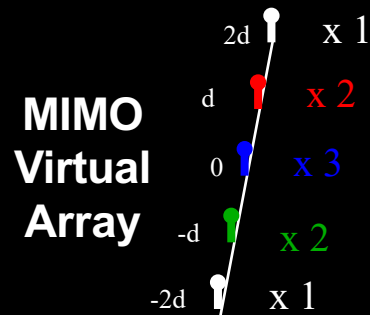


MIMO Radar Channel

Concept of Virtual Array



$$\mathbf{H}(\delta) \propto \begin{pmatrix} e^{i\eta 2d} & e^{i\eta d} & e^{i\eta 0} \\ e^{i\eta d} & e^{i\eta 0} & e^{-i\eta d} \\ e^{i\eta 0} & e^{-i\eta d} & e^{-i\eta 2d} \end{pmatrix} ; \quad \eta = \mathbf{k} \cdot \hat{\mathbf{d}}$$



- Channel estimate provides estimate of MIMO virtual array
- Virtual array may over-represented elements
 - Convolution of real arrays produces virtual array
 - Suggesting sparse arrays

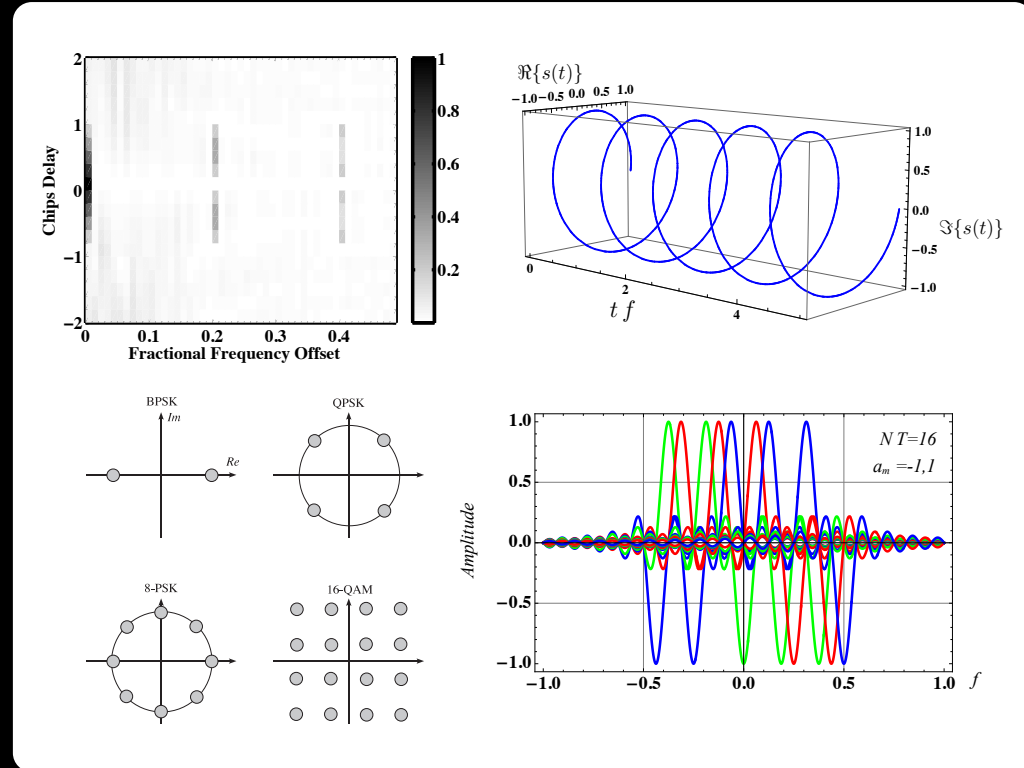
Waveform Issues

Radar Goals

- Desire constant modulus
 - Small peak-to-average power ratio (PAPR)
- Want good complex ambiguity function
 - Large bandwidth
 - Range ambiguities bad
 - Doppler is less clear

Communications Goals

- Make dispersion compensation easy
 - OFDM is popular
- Use convenient modulation
 - Match spectral efficiency needs
- Employ convenient coding and acknowledgement frames



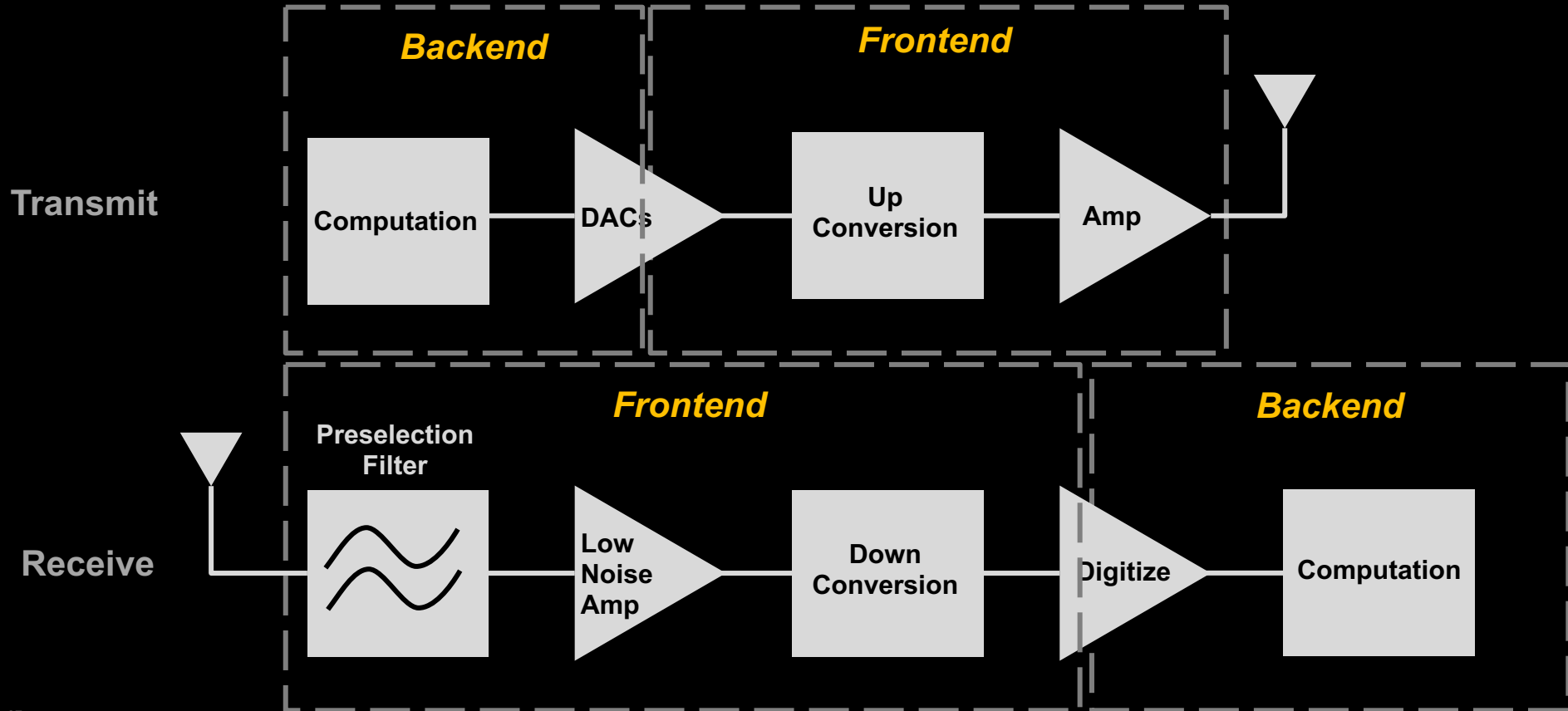
How Do We Get There?

- Review Goals and Implications of Heilmeier Questions
- Underlying Physics of Applications
- **Explore New Enabling Technologies**
- Explore Metrics of Performance
- Investigate Examples



Simple Model of an RF System

- Simplify system to an embarrassing extent
- Identify frontend and backend of system



Novel Flexible Frontends

- Dynamically match spectral use to use
 - Requirements and Environments
- Provide flexible spectral access in presence of in-band or nearby interference
- Reduce need for preselection filters
 - Sensitivity to near-band interference

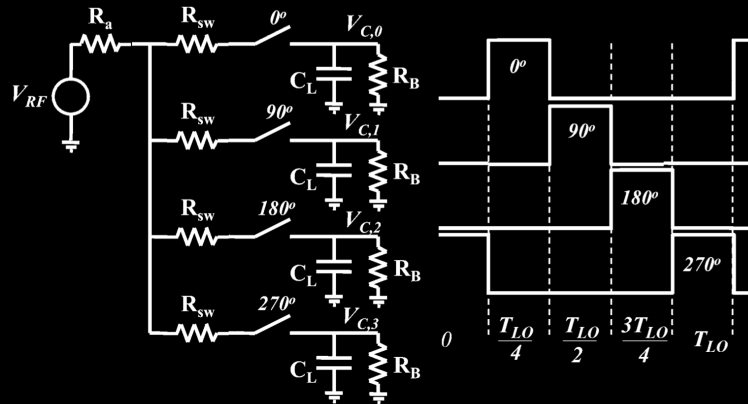
Commercial transceiver
up/down-conversion
and digitization

AD RF
Transceiver
Technology

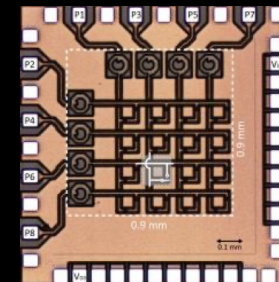
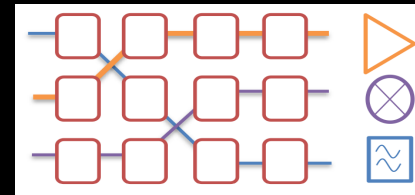


Novel Approaches

Polyphase Mixer



Truly Flexible Frontends
DARPA RF-FPGA



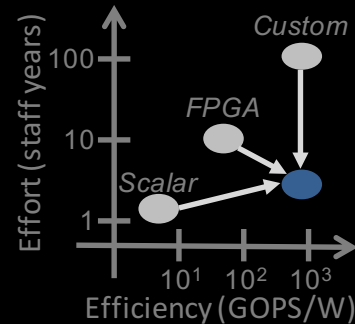
Reinvent Processor Technology

Domain-Focused Advanced Software-Reconfigurable Heterogeneous SoC

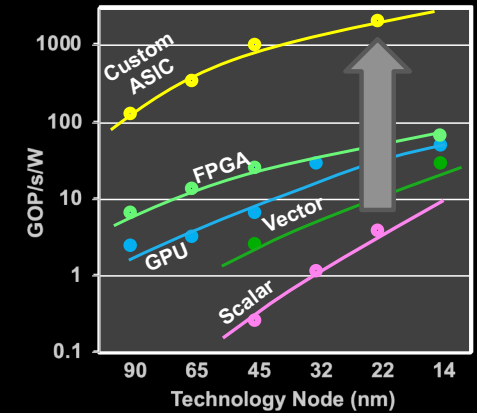
- Enable flexible RF systems
- Leverage and extend next-generation flexible computational architectures
 - Coarse-scale heterogeneous processors
- Simplify use by employing advanced on-chip intelligence and software support



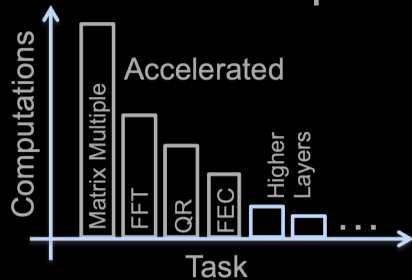
Domain-Specific System-on-Chip (DSSoC)



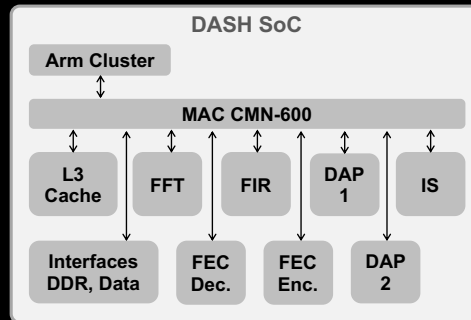
Computational Power Efficiency



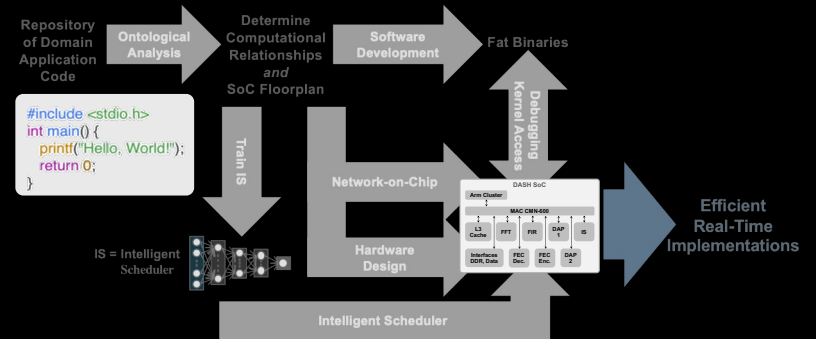
Adaptive Multiple-Antenna Receiver Example



Heterogeneous Processors



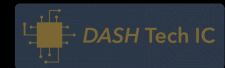
Integrated Framework



Prime



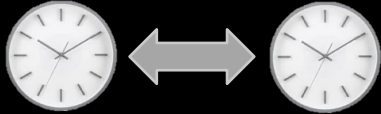
<https://www.youtube.com/watch?v=Z6yDE3TbhcU&t=2620s>



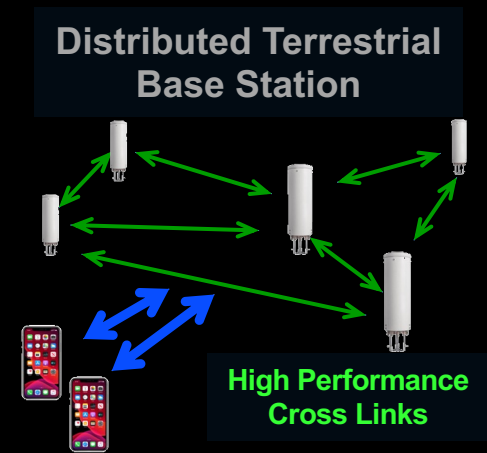
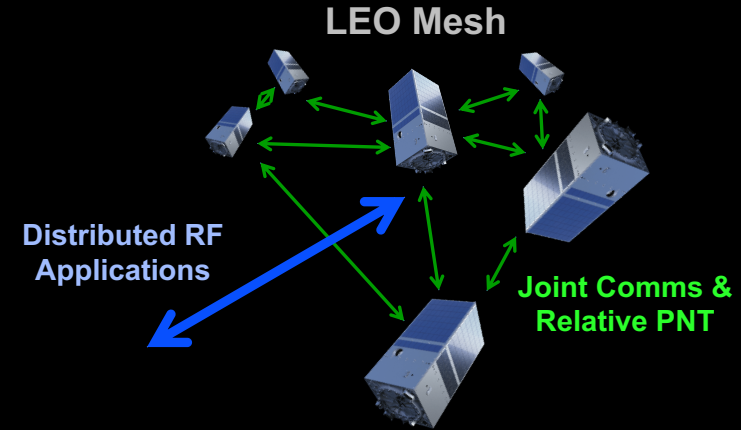
Enabling Novel Distributed RF

- **Develop distributed coherent systems**
 - Distributed space-time transmit and receive beamforming
- **Employ intra-mesh links for precise (phase-accurate) time exchange and data distribution**

Distributed Coherence

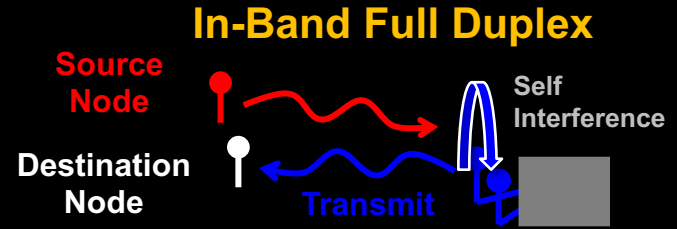


- **Enable new functionality by employing sparse mesh of radios**
 - Enable communications in contested RF environments
 - Increase transmit power (\sim data rate): N^2
 - Increase receive SNR: N
 - Enabling new class of precise multistatic radar systems
- **Requires phase-accurate distributed coherence between radios**



In-Band Full Duplex

- Leverage growing technological base for simultaneous transmit and receive
 - Same time and frequency
 - Easy in principle, insanely difficult in practice
 - Need more than 100 dB of suppression
- Potentially increase throughput by transmitting and receiving at same time
- Enables mix of signaling needs
 - Communications versus sensing
 - Example: using communications signal as monostatic radar



- Mitigate “known” signal
- Compensate for unknown, potentially dynamic channel
 - Mildly dispersive
 - Mildly nonlinear
 - Everything matters

In-Band Full-Duplex Challenges

- Employ in-band full-duplex signaling
 - Same time and frequency
 - Multiple layers of interference mitigation

- Consider simple system model



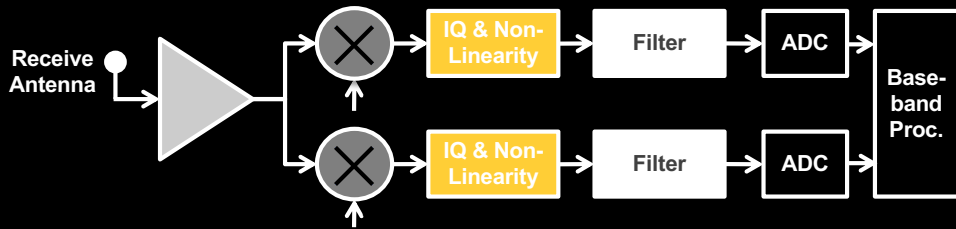
Total Isolation = Spatial Isolation + Processing
Total Goal > 100dB

Temporal Mitigation

$$\tilde{\mathbf{Z}} = \mathbf{Z} \mathbf{P}_S^\perp$$

$$= \mathbf{Z} [\mathbf{I} - \mathbf{S}^\dagger (\mathbf{S} \mathbf{S}^\dagger)^{-1} \mathbf{S}]$$

- Consider one of many complications
 - Mild receive nonlinearities
 - IQ Mismatch



Self-Interference

Channel Baseband Signal

IQ Mismatch

$$z(t) = \Re\{h x(t)\} + i \Im\{h x(t)\} (1 + \epsilon) - \frac{\alpha_{\Re}}{\sigma_{\text{rx}}^2} (\Re\{h x(t)\})^3 - i \frac{\alpha_{\Im}}{\sigma_{\text{rx}}^2} (\Im\{h x(t)\})^3 - \mathcal{O}(h x(t))^5 + n(t)$$

When You Don't Know the Answer, Invoke ML

- **Use ML to approximate high-dimensional nonlinear functions**
 - Wide range of recent advances in parameter estimation and processing
 - Applicable to wide range of nonlinear functions
 - D. Elbrächter, D. Perekrestenko, P. Grohs, H. Bölcskei, “Deep neural network approximation theory,” IEEE Transactions on Information Theory, 2021
- **Understand implications of model mismatch**
 - **“Currently, artificial intelligence (AI) is remarkably stupid, sometimes useful, but stupid. It is important to remember that machine learning (ML), which presently is most of AI, is just "curve fitting" in a high-dimensional space that you cannot visualize using basis functions that you cannot understand. ML itself has no actual understanding. Furthermore, without serious analysis of ML's robustness and interpretability, you have no chance of knowing if what it produces is valid or good-looking lies. Basic theory on ML robustness and interpretability is still very weak. You have been warned.” – Dan Bliss**

Interesting ML Applications

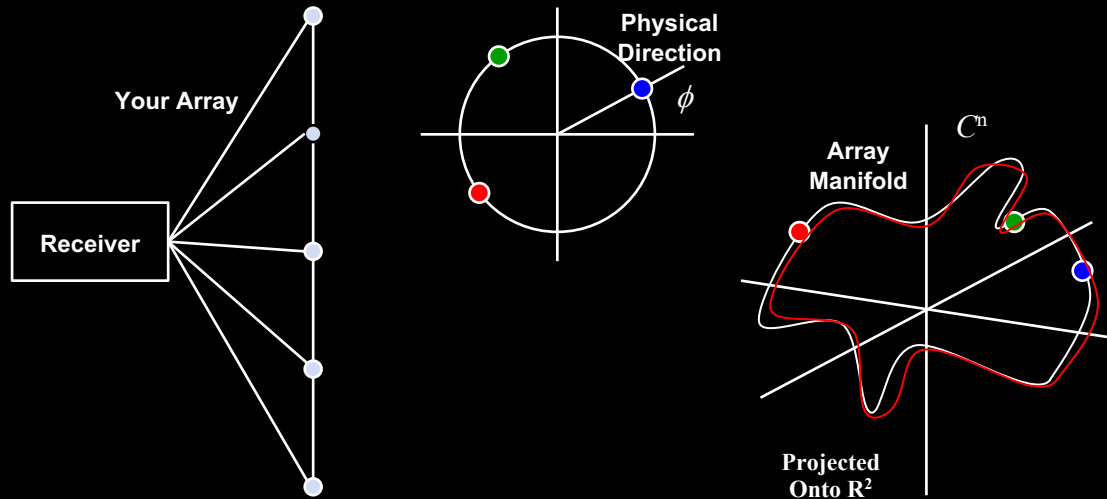
- **Identify the right applications**

- Resource optimization

- Approximate full searches
- Much faster than traveling salesperson search

- Manifold learning

- Antenna array calibration, particularly in complicated environments
- Connect to partial physical knowledge



How Do We Get There?

- Review Goals and Implications of Heilmeier Questions
- Underlying Physics of Applications
- Explore New Enabling Technologies
- **Explore Metrics of Performance**
- Investigate Examples



What Are We Doing?

- Move information
- Detect states or objects
- Estimate parameters
- Track parameter evolution
- Operate in presence of noise

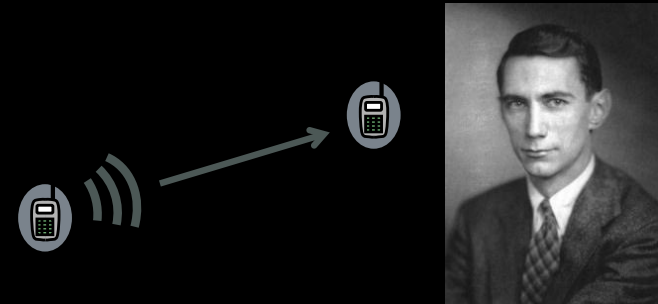
**Drives Us to Explore
Detection and Estimation
Theory**



Communications Information Bound

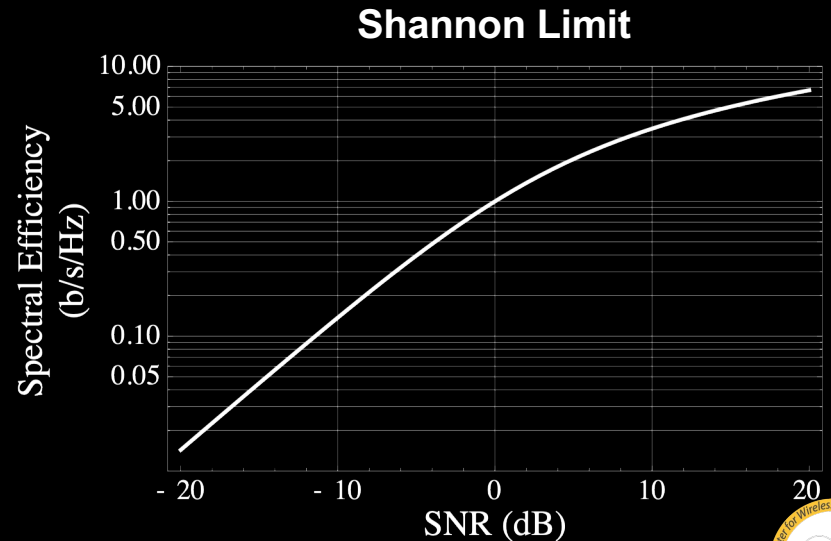
- Move bits from one place to another
- Specify model
 - Amplitude domain
- Identify limits to performance
 - Ratio of signal power to noise power is key
 - Known as channel capacity or Shannon Limit

$$\text{Received Signal } z(t) = \underbrace{a}_{\text{Attenuation}} \underbrace{s(t)}_{\text{Transmitted Signal}} + \underbrace{n(t)}_{\text{Noise}}$$



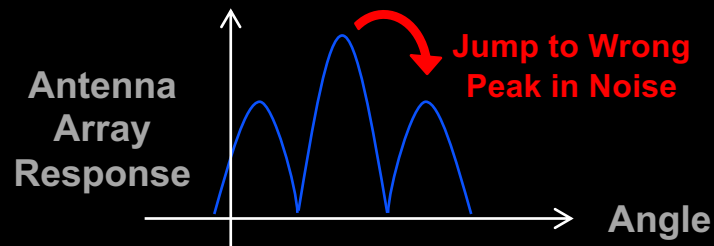
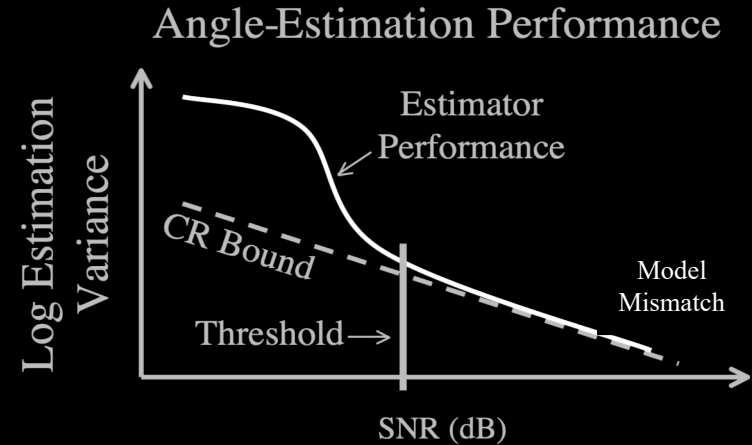
$$\text{Channel Capacity (b/s)} \quad C \leq \underbrace{B}_{\text{Total Bandwidth}} \log_2 \left(1 + \underbrace{\text{SNR}}_{\text{SNR} = \frac{P_{\text{signal}}}{P_{\text{noise}}}} \right)$$

- Spectral efficient is C/B



Parameter Estimation Performance

- Performance of estimator as a function of
 - SNR
 - Integrated SNR
- Typical estimator performance
 - Asymptotic region
 - Transition region
 - Random region
- Above some threshold point “good” estimator performance approaches Cramer-Rao bound
 - Cramer-Rao ignores large errors
 - Nonlocal error bounds exist (Weiss-Weinstein, Method of Interval Errors)



Estimator Variance

- Consider random variable

$$x \sim \underbrace{p(x; \theta)}$$

Probability Density Function

- Assume single parameter of interest

$$\theta$$

- Estimator of parameter based on sequence of observations

$$\hat{\theta} = f(x_1, x_2, x_3, \dots)$$

- Variance of estimation

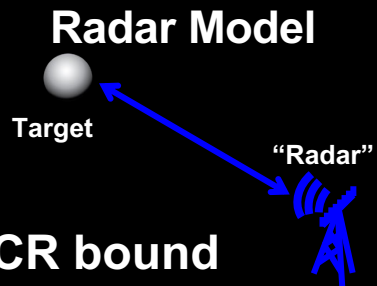
$$\begin{aligned} \text{var}(\hat{\theta}) &= \langle (\hat{\theta} - \theta)^2 \rangle \\ &= \int dx (\hat{\theta} - \theta)^2 p(x; \theta) \end{aligned}$$

Note:
*Do Not Confuse
Signal Variance
with
Parameter Estimation
Variance*

Cramer-Rao Bound

Model

- Radar estimates range and Doppler of target
 - Simple universe
 - Nonfluctuating target (signal in the mean)



$$r = \frac{c}{2} \tau$$

$$z(t) = b s(t - \tau) + n(t)$$
$$= \underbrace{a}_{\text{Parameters}} e^{i\phi} s(t - \underbrace{\tau}_{\text{Parameters}}) + n(t)$$

- Multivariate CR bound
 - Evaluate delay estimation bound and convert to range

$$\text{cov}\{\hat{\boldsymbol{\theta}}\} = \left\langle (\hat{\boldsymbol{\theta}} - \boldsymbol{\theta})(\hat{\boldsymbol{\theta}} - \boldsymbol{\theta})^T \right\rangle$$

$$\geq \underbrace{\mathbf{J}^{-1}}$$

Inverse of
Fisher Information
Matrix

$$\{\mathbf{J}\}_{m,n} = \left\langle \left(\frac{\partial}{\partial \{\boldsymbol{\theta}\}_m} \log p(\mathbf{z}; \boldsymbol{\theta}) \right) \left(\frac{\partial}{\partial \{\boldsymbol{\theta}\}_n} \log p(\mathbf{z}; \boldsymbol{\theta}) \right) \right\rangle$$
$$= - \left\langle \frac{\partial^2 \log p(\mathbf{z}; \boldsymbol{\theta})}{\partial \{\boldsymbol{\theta}\}_m \partial \{\boldsymbol{\theta}\}_n} \right\rangle$$

Model

- **Three parameters**

- Delay
- Amplitude
- Phase

$$\begin{aligned} z(t) &= b s(t - \tau) + n(t) \\ &= \underbrace{a}_{\text{Amplitude}} e^{i \underbrace{\phi}_{\text{Phase}}} s(t - \underbrace{\tau}_{\text{Delay}}) + n(t) \end{aligned}$$

Parameters

- **Sampled multivariate complex Gaussian PDF**

$$\begin{aligned} p(\underline{\mathbf{z}}; \tau, a, \phi) &= \frac{1}{(\pi \sigma_n^2)^{n_s}} e^{-\{(\underline{\mathbf{z}} - a e^{i\phi} \underline{\mathbf{s}}_\tau) (\underline{\mathbf{z}} - a e^{i\phi} \underline{\mathbf{s}}_\tau)^\dagger / \sigma_n^2\}} \\ &= \frac{1}{(\pi \sigma_n^2)^{n_s}} e^{-\sum_m \|z(mT_s) - a e^{i\phi} s(mT_s - \tau)\|^2 / \sigma_n^2} \end{aligned}$$

- **Observe signal is in the mean**

$$\underline{\boldsymbol{\mu}} = a e^{i\phi} \underline{\mathbf{s}}(t - \tau)$$

- **Estimate delay by maximizing likelihood**

$$\hat{\tau} = \operatorname{argmax}_{\tau; a, \phi} p(\underline{\mathbf{z}}; \tau, a, \phi)$$

Delay Bound

- **Adjust parameter origins to zero off-diagonal elements**
 - Just need to worry about delay term

$$\mathbf{J} = \begin{pmatrix} J_{\tau,\tau} & 0 & 0 \\ 0 & J_{a,a} & 0 \\ 0 & 0 & J_{\phi,\phi} \end{pmatrix}$$

Fisher Information Matrix

- **Go back to standard definition**

$$J_{\tau,\tau} = \left\langle \left(\frac{\partial}{\partial \tau} \log p(z; \tau, a, \phi) \right) \left(\frac{\partial}{\partial \tau} \log p(z; \tau, a, \phi) \right)^* \right\rangle$$

- **Derivative with respect to delay**

$$\begin{aligned} \frac{\partial}{\partial \tau} \log p &= - \sum_m [n^*(m T_s) a e^{i\phi} \frac{\partial}{\partial \tau} s(m T_s - \tau) + n(m T_s) a e^{-i\phi} \frac{\partial}{\partial \tau} s^*(m T_s - \tau)] \\ &= - \sum_m [n^*(m T_s) a e^{i\phi} \frac{\partial}{\partial \tau} s(m T_s - \tau) + c.c.] \end{aligned}$$

Evaluate Delay CRB

- **Basic derivation**

$$\begin{aligned}
 J_{\tau,\tau} &= \left\langle \left(\frac{\partial \log p(\mathbf{z}_\tau)}{\partial \tau} \right)^2 \right\rangle \\
 &= \left\langle \left\| \sum_m [n^*(mT_s) a e^{i\phi} \frac{\partial}{\partial \tau} s(mT_s - \tau) + c.c.] \right\|^2 \right\rangle \\
 &= 2 \sum_m \left\langle n^*(mT_s) a e^{i\phi} \frac{\partial}{\partial \tau} s(mT_s - \tau) [n(mT_s) a e^{-i\phi} \frac{\partial}{\partial \tau} s^*(mT_s - \tau)] \right\rangle \\
 &= 2 a^2 \sum_m \left\langle \frac{\partial}{\partial \tau} s(mT_s - \tau) \frac{\partial}{\partial \tau} s^*(mT_s - \tau) \right\rangle
 \end{aligned}$$

- **Leverage Parseval**

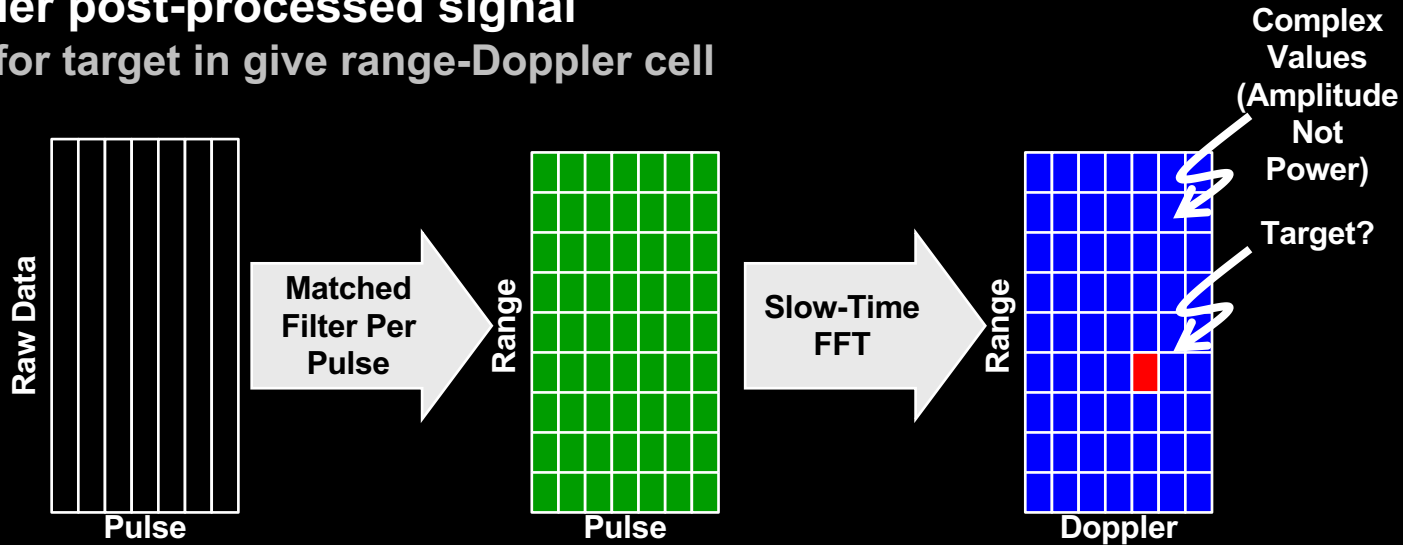
$$\begin{aligned}
 \left\langle \left\| \frac{\partial}{\partial \tau} s(mT_s - \tau) \right\|^2 \right\rangle &= \langle \| -2\pi f i S(-f) e^{-i2\pi m T_s} \|^2 \rangle \\
 &= (2\pi)^2 \langle \| f S(f) \|^2 \rangle \\
 &= (2\pi)^2 B_{\text{rms}}^2 \langle \| S(f) \|^2 \rangle \\
 &= (2\pi)^2 B_{\text{rms}}^2 \langle \| s(mT_s - \tau) \|^2 \rangle = (2\pi)^2 B_{\text{rms}}^2
 \end{aligned}$$

$$\begin{aligned}
 B_{\text{rms}}^2 &= \frac{\langle \| f S(f) \|^2 \rangle}{\langle \| S(f) \|^2 \rangle} \\
 \langle f \| S(f) \|^2 \rangle &= 0
 \end{aligned}$$

$$\begin{aligned}
 \frac{1}{J_{\tau,\tau}} &= \frac{1}{2 a^2} \frac{1}{(2\pi)^2 B_{\text{rms}}^2} \\
 &= \frac{1}{8\pi^2 B_{\text{rms}}^2} \frac{1}{\text{ISNR}}
 \end{aligned}$$

Neyman-Pearson Analysis for Nonfluctuating Target Under Range-Doppler Processing

- Consider deterministic, nonfluctuating target
- Consider post-processed signal
 - Test for target in give range-Doppler cell



- Find likelihood ratio test (NP)
- Evaluate ROC

Nonfluctuating Target

Probability Densities

- **Neyman-Pearson**
 - Use log likelihood ratio

$$L = \log_e \left[\frac{p(z|H_1)}{p(z|H_0)} \right]$$

- **Noise, H_0**

$$p(z) = \frac{1}{\pi \sigma_n^2} e^{-\|z\|^2 / \sigma_n^2}$$

- **Noise plus deterministic target, H_1**

- Ricean (sort of square root of noncentral Chi square with 2 degrees)

$$p(z) = \frac{1}{\pi \sigma_n^2} e^{-(\|z\|^2 + \mu^2) / \sigma_n^2} I_0 \left(\frac{2\mu \|z\|}{\sigma_n^2} \right)$$

Target Mean
At Output of Processing

Modified Bessel Function
Of First Kind

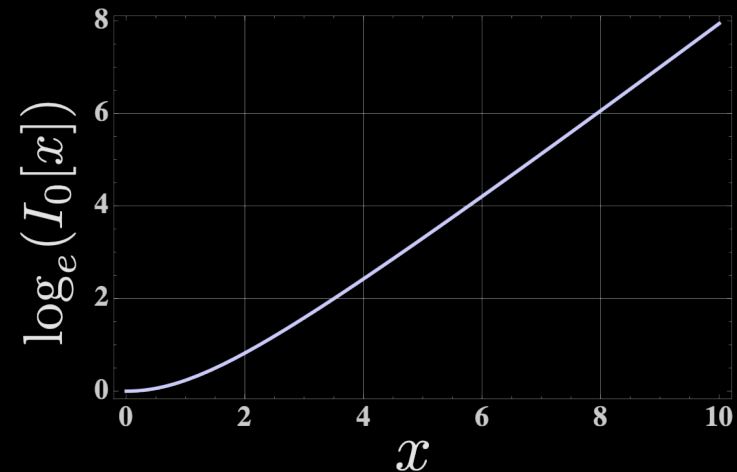
Nonfluctuating Target

Neyman-Pearson

- Compare likelihoods
 - Use log likelihood ratio

$$\begin{aligned} L &= \log_e \left[\frac{p(z|H_1)}{p(z|H_0)} \right] \leq \log_e(\eta) \\ &= \log_e \left[\frac{\frac{1}{\pi \sigma_n^2} e^{-(\|z\|^2 + \mu^2)/\sigma_n^2} I_0\left(\frac{2\mu\|z\|}{\sigma_n^2}\right)}{\frac{1}{\pi \sigma_n^2} e^{-\|z\|^2/\sigma_n^2}} \right] \leq \log_e(\eta) \\ &= \log_e \left[e^{-(\mu^2)/\sigma_n^2} I_0\left(\frac{2\mu\|z\|}{\sigma_n^2}\right) \right] \leq \log_e(\eta) \\ &= \log_e \left[I_0\left(\frac{2\mu\|z\|}{\sigma_n^2}\right) \right] - \mu^2/\sigma_n^2 \leq \log_e(\eta) \\ &= \log_e \left[I_0\left(\frac{2\mu\|z\|}{\sigma_n^2}\right) \right] \leq \log_e(\eta) + \mu^2/\sigma_n^2 = \eta' \end{aligned}$$

- Monotonic, really just use $\|z\| \leq \eta''$



Nonfluctuating Target

Magical Knowledge Performance, $P_{FA} - P_D$

- Test signal within a range-Doppler bin

– Variable that we care about $x = \|z\|$, or $q = \|z\|^2$

- H_0 , Noise

– Rayleigh,

$$p(x|H_0) = \frac{2x}{\sigma_n^2} e^{-x^2/\sigma_n^2}$$

$$\begin{aligned} P_{FA} &= \int_{\eta}^{\infty} dx p(x|H_0) \\ &= \int_{\eta}^{\infty} dx \frac{2x}{\sigma_n^2} e^{-x^2/\sigma_n^2} \\ &= e^{-\eta^2/\sigma_n^2} \end{aligned}$$

$$\eta = \sigma_n \sqrt{-\log_e(P_{FA})}$$

**Closed-Form
Threshold**

- H_1 , Nonfluctuating signal plus noise

– Could use noncentral Chi square

– Ricean,

$$p(x|H_1) = \frac{2x}{\sigma_n^2} e^{-(x^2+\mu^2)/\sigma_n^2} I_0\left(\frac{2\mu^2 x}{\sigma_n^2}\right)$$

$$\begin{aligned} P_D &= \int_{\eta}^{\infty} dx p(x|H_1) \\ &= \int_{\eta}^{\infty} dx \frac{2x}{\sigma_n^2} e^{-(x^2+\mu^2)/\sigma_n^2} I_0\left(\frac{2\mu^2 x}{\sigma_n^2}\right) \\ &= Q_M\left(\sqrt{\frac{2\mu^2}{\sigma_n^2}}, \sqrt{\frac{2\eta^2}{\sigma_n^2}}\right) \end{aligned}$$

$$Q_M(\alpha, T) = \int_T^{\infty} dt t e^{-(t^2+\alpha^2)/2} I_0(\alpha t)$$

Marcum Q-Function



Nonfluctuating Target

Magical Knowledge Performance, P_D - P_{FA}

- Evaluate receiver operating characteristics (ROC) curve False alarm

- Probability of false alarm

$$P_{FA} = e^{-\eta^2/\sigma_n^2}$$

$$\eta = \sigma_n \sqrt{-\log_e(P_{FA})}$$

- Probability of detection

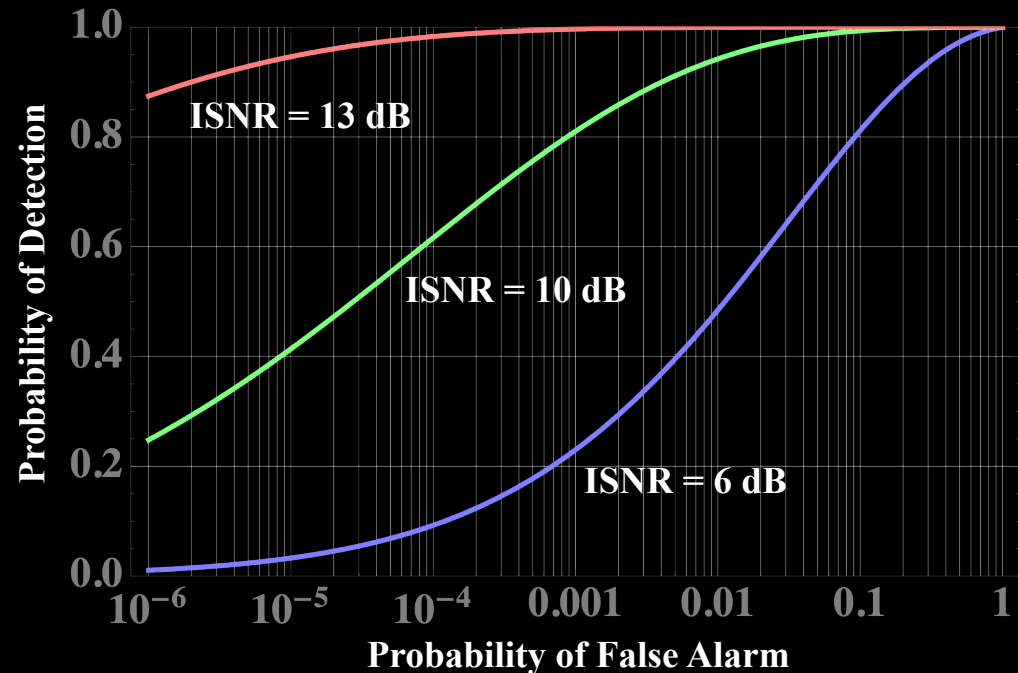
$$P_D = Q_M\left(\sqrt{\frac{2\mu^2}{\sigma_n^2}}, \sqrt{\frac{2\eta^2}{\sigma_n^2}}\right)$$

- Q_M is Marcum Q-function

- Put it all together

$$P_D = Q_M\left(\sqrt{2\text{ISNR}}, \sqrt{-2\log_e(P_{FA})}\right)$$

$$\text{ISNR} = \frac{\mu^2}{\sigma_n^2}$$



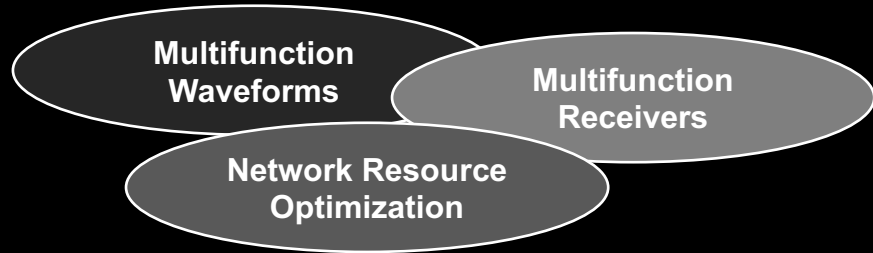
How Do We Get There?

- Review Goals and Implications of Heilmeier Questions
- Underlying Physics of Applications
- Explore New Enabling Technologies
- Explore Metrics of Performance
- **Investigate Examples**

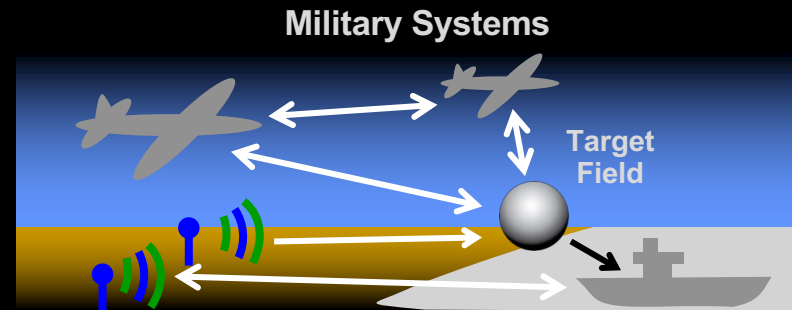
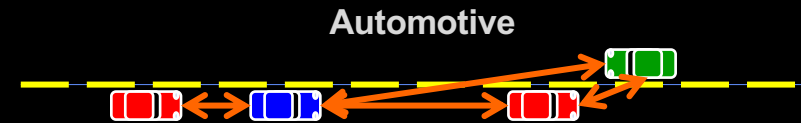


Spectral Convergence

- **Reuse RF/mmWave signals and receivers**
 - Node performs multiple tasks simultaneously with same energy
 - Remove artificial separation between communications, sensing, PNT, etc.



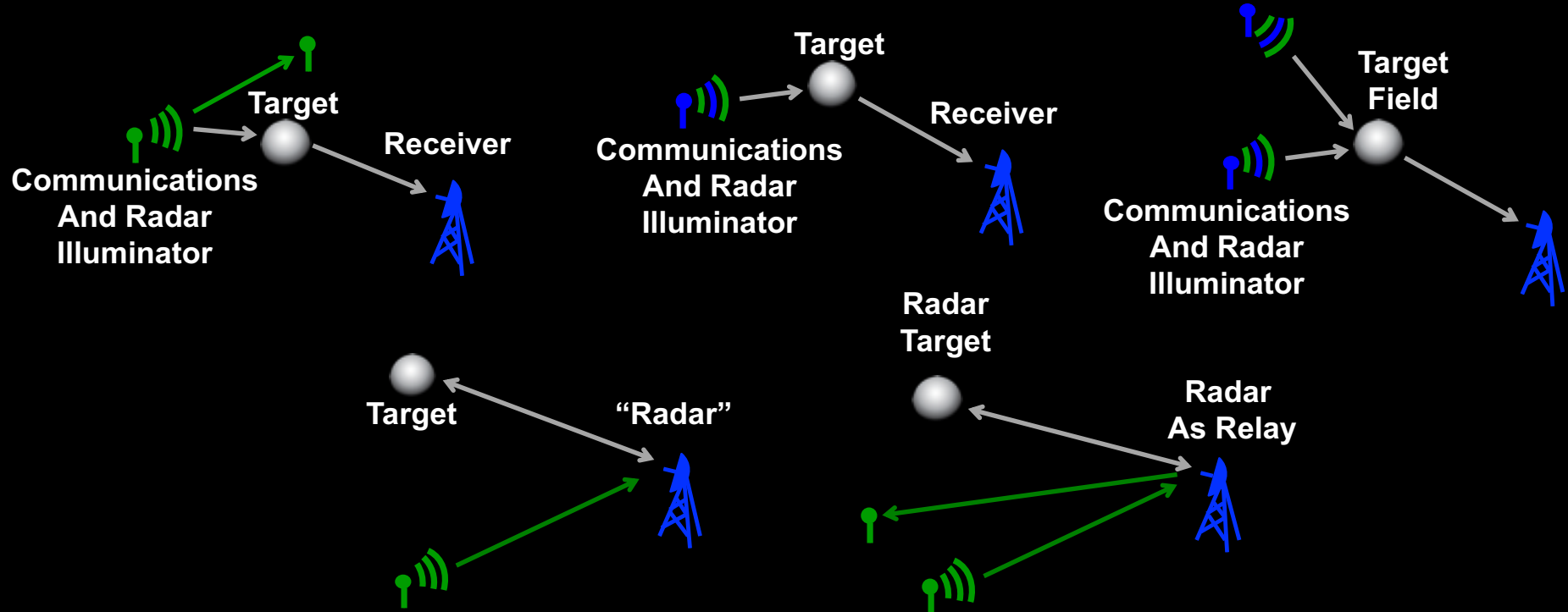
- **Improve rather than degrade performance by friendly RF/mmWave systems**
 - Radios can do everything
- **Enabled by recent technical advances**
 - Efficient flexible computational systems
 - Flexible RF



Simple Topological Models

Communications and Radar Examples

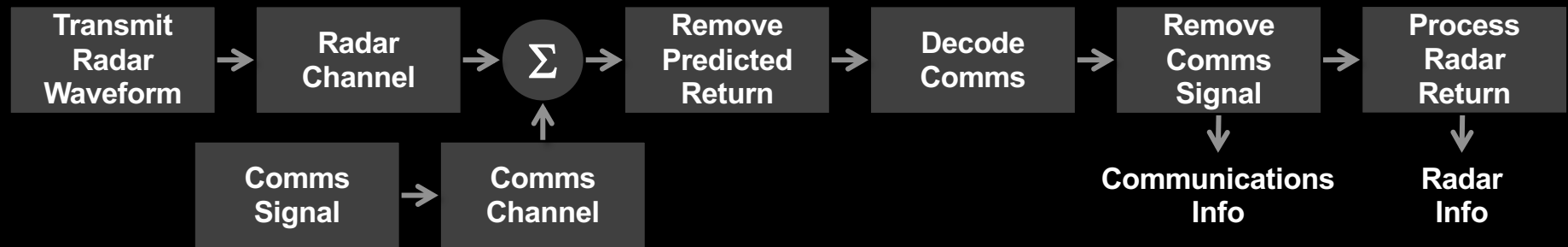
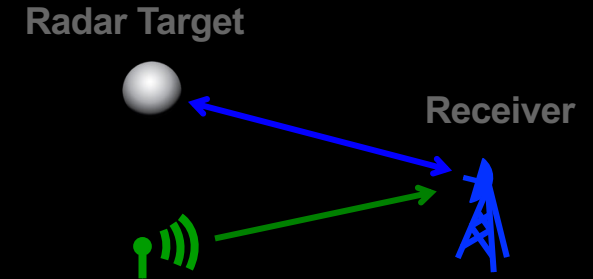
Decompose more complicated networks into basic components



Multi-Access Communications & Radar

Example Approach

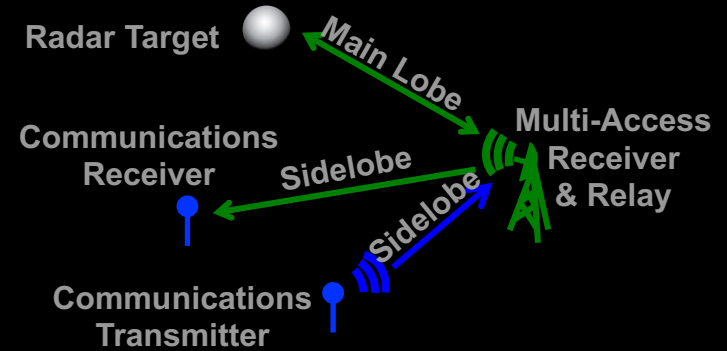
- Recover radar return and communications simultaneously
- Explore joint estimation, detection and information theory
 - Interactions between sensing and communications



Multi-Access Receive and Relay

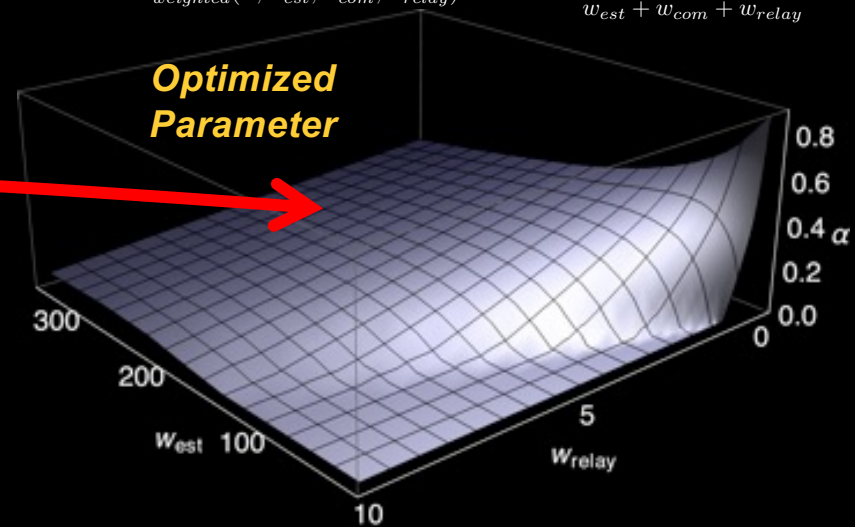
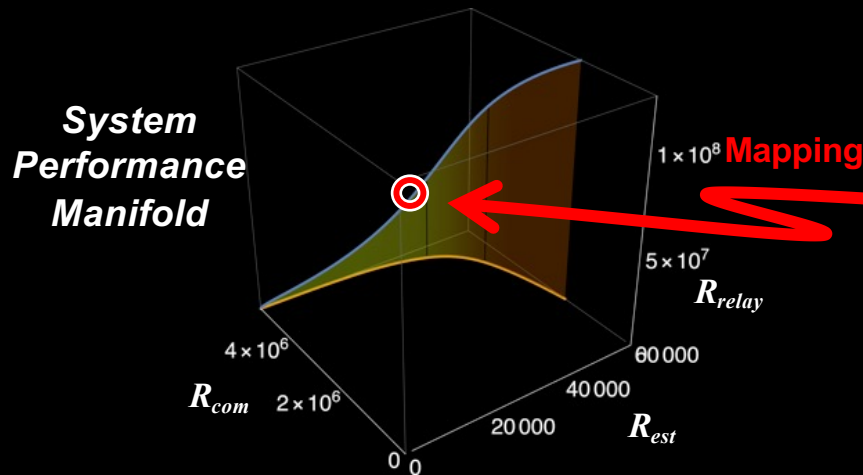
Simple Example

- **Optimize operating point**
 - Maximize objective function
- **Evaluate theoretical joint manifold**
- **Investigate operating point selection**
 - Simple example: multi-access receive and relay
 - Simple objective function



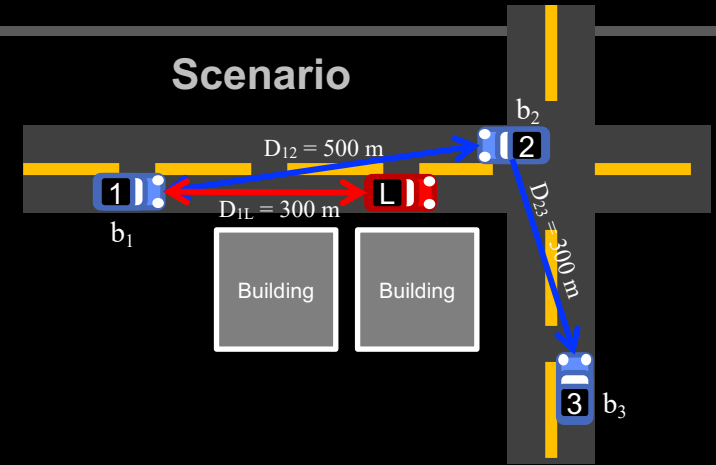
$$\hat{\alpha} = \operatorname{argmax}_{\alpha} \{R_{weighted}(\alpha; w_{est}, w_{com}, w_{relay})\}$$

$$R_{weighted}(\alpha; w_{est}, w_{com}, w_{relay}) = \frac{w_{est} R_{est} + w_{com} R_{com} + w_{relay} R_{relay}}{w_{est} + w_{com} + w_{relay}}$$



Toy Automotive Problem

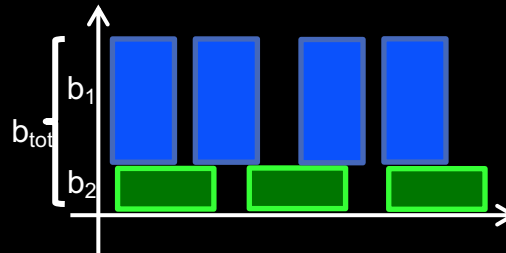
- Consider joint communications; radar; and positioning, navigation, and timing (PNT) problem
- Communicate to Car 3 that legacy (L) vehicle is approaching intersection
- Use waveforms for comms, radar, and PNT
- Trade bandwidth between users



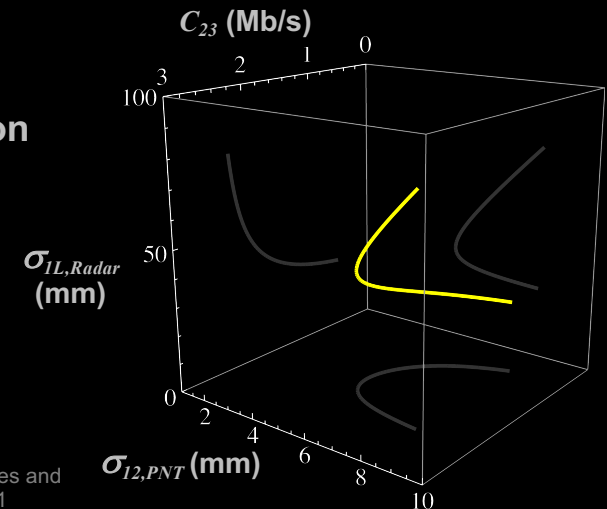
Parameters

- Center frequency = 77 GHz
- Total bandwidth (1&2) = 1 GHz,
- Transmit power = 1W
- Noise figure = 6 dB, T = 300K
- Coding loss = -6 dB
- Chirp TBP = 30 dB, Slow-time TBP = 20 dB
- PNT TBP = 100 chirps
- RCS = 10 m²
- Antenna gain
 - 13dB (forward)
 - (1 ↔ 2) = 0 dB, (2 → 3) = -6 dB, (3 → 2) = 0 dB,

Chirp Pulse Position Modulation



Performance Manifold



Multiple Access Communications Bound

Illustrative Analogy

- Satisfy all bound

$$R_1 \leq \log_2(1 + a_1^2 P_1)$$

$$R_2 \leq \log_2(1 + a_2^2 P_2)$$

$$R_1 + R_2 \leq \log_2(1 + a_1^2 P_1 + a_2^2 P_2)$$

– Fix power of channel for both transmitters

- Find points of bound intersection

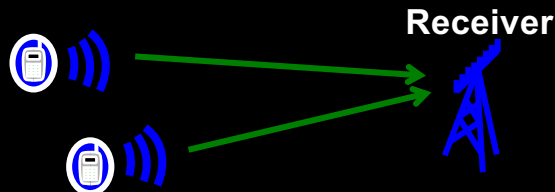
$$R_2 = \log_2(1 + a_2^2 P_2)$$

$$R_1 + R_2 - R_2 = \log_2(1 + a_1^2 P_1 + a_2^2 P_2) - \log_2(1 + a_2^2 P_2)$$

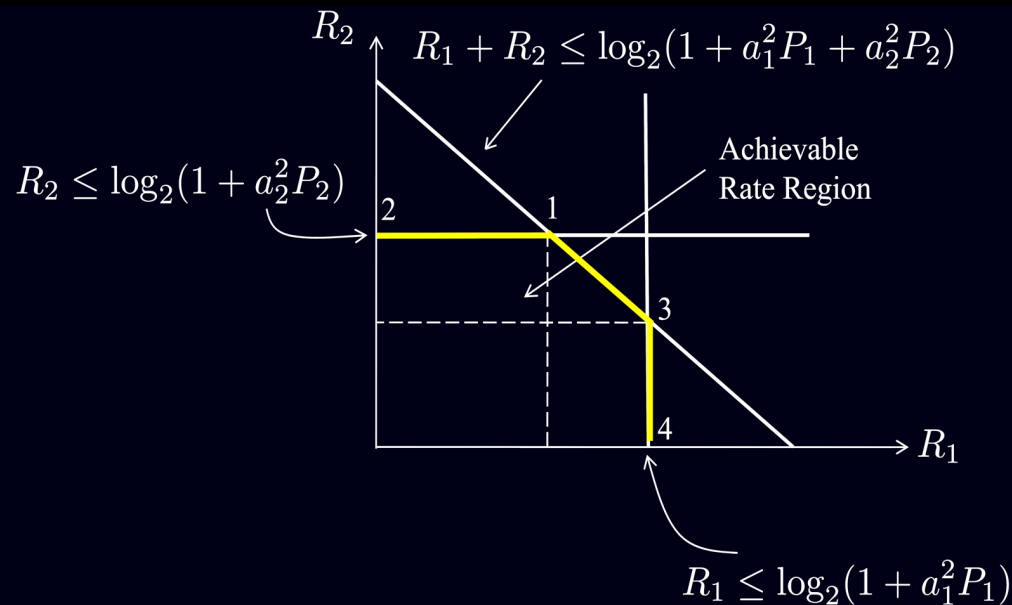
$$R_1 = \log_2\left(\frac{1 + a_1^2 P_1 + a_2^2 P_2}{1 + a_2^2 P_2}\right)$$

$$\{R_1, R_2\} = \left\{ \log_2\left(1 + \frac{a_1^2 P_1}{1 + a_2^2 P_2}\right), \log_2(1 + a_2^2 P_2) \right\}$$

$$\{R_1, R_2\} = \left\{ \log_2(1 + a_1^2 P_1), \log_2\left(1 + \frac{a_2^2 P_2}{1 + a_1^2 P_1}\right) \right\}$$



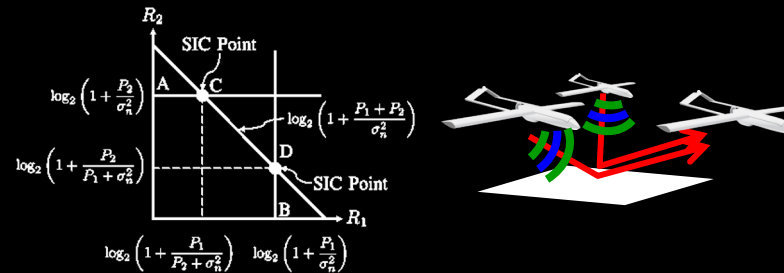
Multiple Access Bound



Multiuser Communications & Multi-Static SAR

MATLAB Simulation

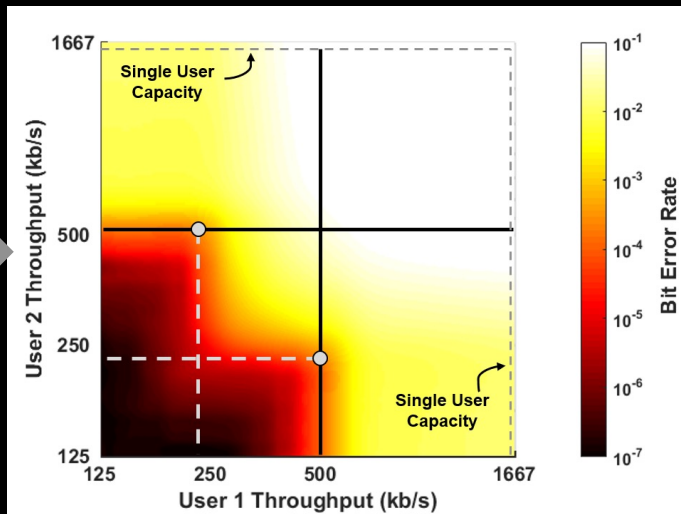
- Design joint radar-communications system
- Develop multi-static channel model
- Approach performance bounds
- Perform SAR imaging



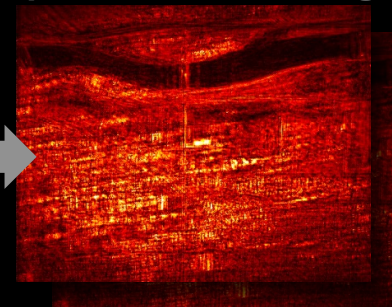
Modeled Scattering Field



Successive Interference Cancellation



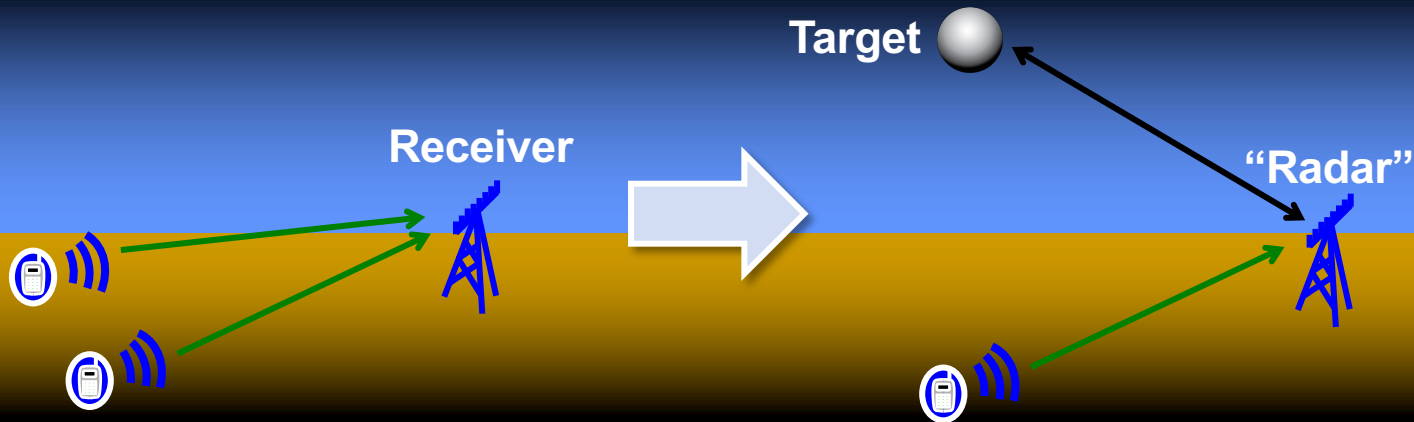
Multi-Static Synthetic Aperture Radar Image



Multiple Access Radar/Comms Receiver

Are The Bounds Equivalent?

- **Equivalent? No**
 - Estimation is not drawn from countable distribution
 - Bound is not achievable



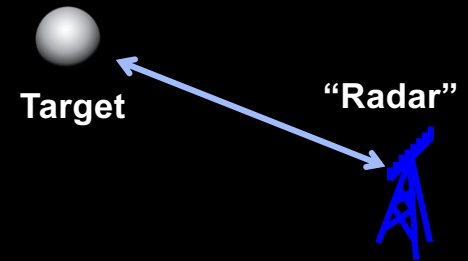
- **But, let's see how close we can get**
 - Focus on achievable (inner) bounds

Hint:
We Will Apply MUD to
Mixed Radar and
Communications

Characterize What You Have Learned about the Target

Random Process Characterization

- **Develop concept of estimation information rate**
 - Average bit rate required to encode knowledge of target
- **Estimate target range (delay)**
- **Assume delay determined by partially known random process**
 - Assume unknown delay is Gaussian



Target Delay

$$\tau_m^{(k)} = \tau_{m,\text{pre}}^{(k)} + n_{\tau,\text{proc}}$$

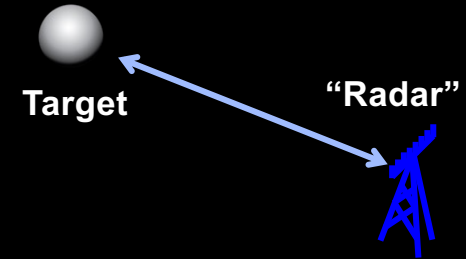
Target Delay Variance

$$\sigma_{\text{proc}}^2 = \langle n_{\tau,\text{proc}}^2 \rangle$$



Range (Delay) Estimation Uncertainty

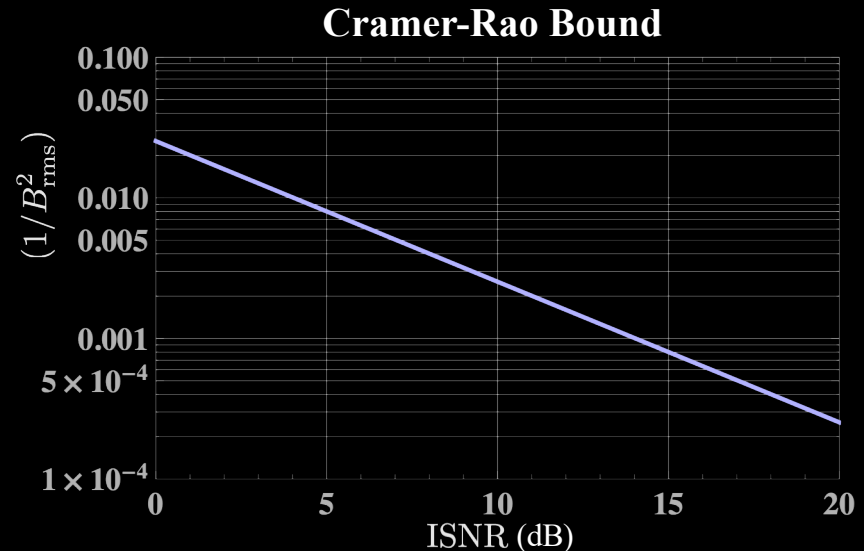
- Assume good estimator and reasonable integrated SNR
- Use Cramer-Rao bound to get delay estimation performance bound



$$\sigma_{\tau; \text{est}}^2 = \left(\frac{1}{8\pi^2 B_{\text{rms}}^2 \text{ISNR}} \right)$$

$$B_{\text{rms}}^2 = \frac{\int df f^2 \|X(f)\|^2}{\int df \|X(f)\|^2}$$

$$\langle f \rangle = 0$$



Target Information Rate

A Quirky Parameterization

- **Invent target estimation rate**
 - Assume process variation and estimation error are Gaussian
- **Determine estimation information rate by evaluating total and estimation entropies**
 - $R_{\text{est}} \sim H_{\text{uncertainty}} - H_{\text{est}}$
 - Average number of bits required to encode estimate per unit time

$$R_{\text{est}} \leq \sum_m \frac{\delta}{2T} \log_2 \left(1 + \frac{\sigma_{\tau_m, \text{proc}}^2}{\sigma_{\tau_m, \text{est}}^2} \right)$$

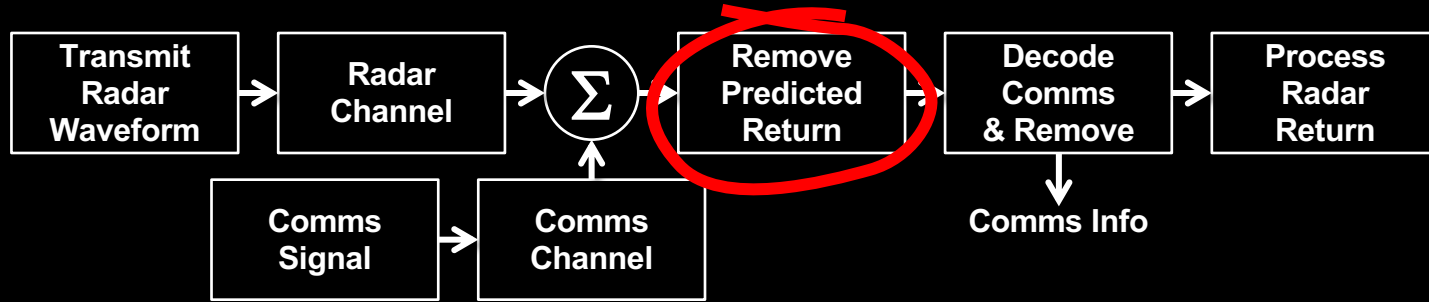
- **Ratio of variances looks like an “SNR”**

- Like SNR $\frac{\sigma_{\tau, \text{proc}}^2}{\sigma_{\tau, \text{est}}^2}$

Bound Approach Overview

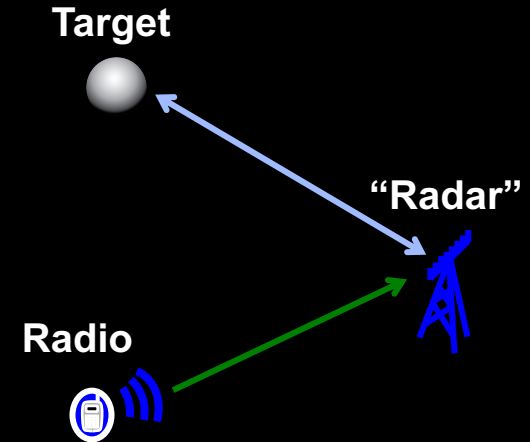
Successive Interference Cancellation

- Construct novel joint radar/communications approach



- Basic successive interference cancellation (SIC) bound

- Define radar random process
- Evaluate estimation error of radar
- Evaluate estimation information rate
- Evaluate communications capacity
- Evaluate SIC point
- Interpolate between SIC point and communications-only point



Received Signal After Predicted Radar Return Removed

- Received signal combines radar return and communications signal

$$z(t) = \sqrt{P_{\text{com}}} b s_{\text{com}}(t) + \sqrt{P_{\text{radar}}} \sum_{m=1}^N a_m s_{\text{radar}}(t - \tau_m) + n(t)$$

- Remove predicted radar return

$$\tilde{z}(t) = \sqrt{P_{\text{com}}} b s_{\text{com}}(t) + n(t) + \sqrt{P_{\text{radar}}} \sum_{m=1}^N a_m [s_{\text{radar}}(t - \tau_m) - s_{\text{radar}}(t - \tau_{m,\text{pre}})]$$

- Approximate difference with derivative

$$\tilde{z}(t) \approx \sqrt{P_{\text{com}}} b s_{\text{com}}(t) + n(t) + \sqrt{P_{\text{radar}}} \sum_{m=1}^N a_m \frac{\partial s_{\text{radar}}(t - \tau_m)}{\partial t} n_{\tau,\text{proc}}$$

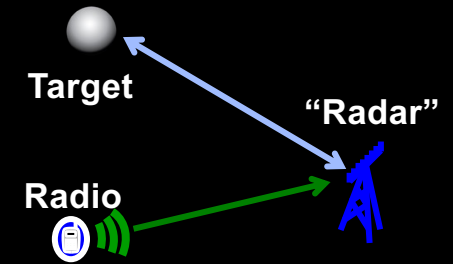
Not Required,
But Provides
Nice Result

- Characterize “noise” to communications decoder at “radar”

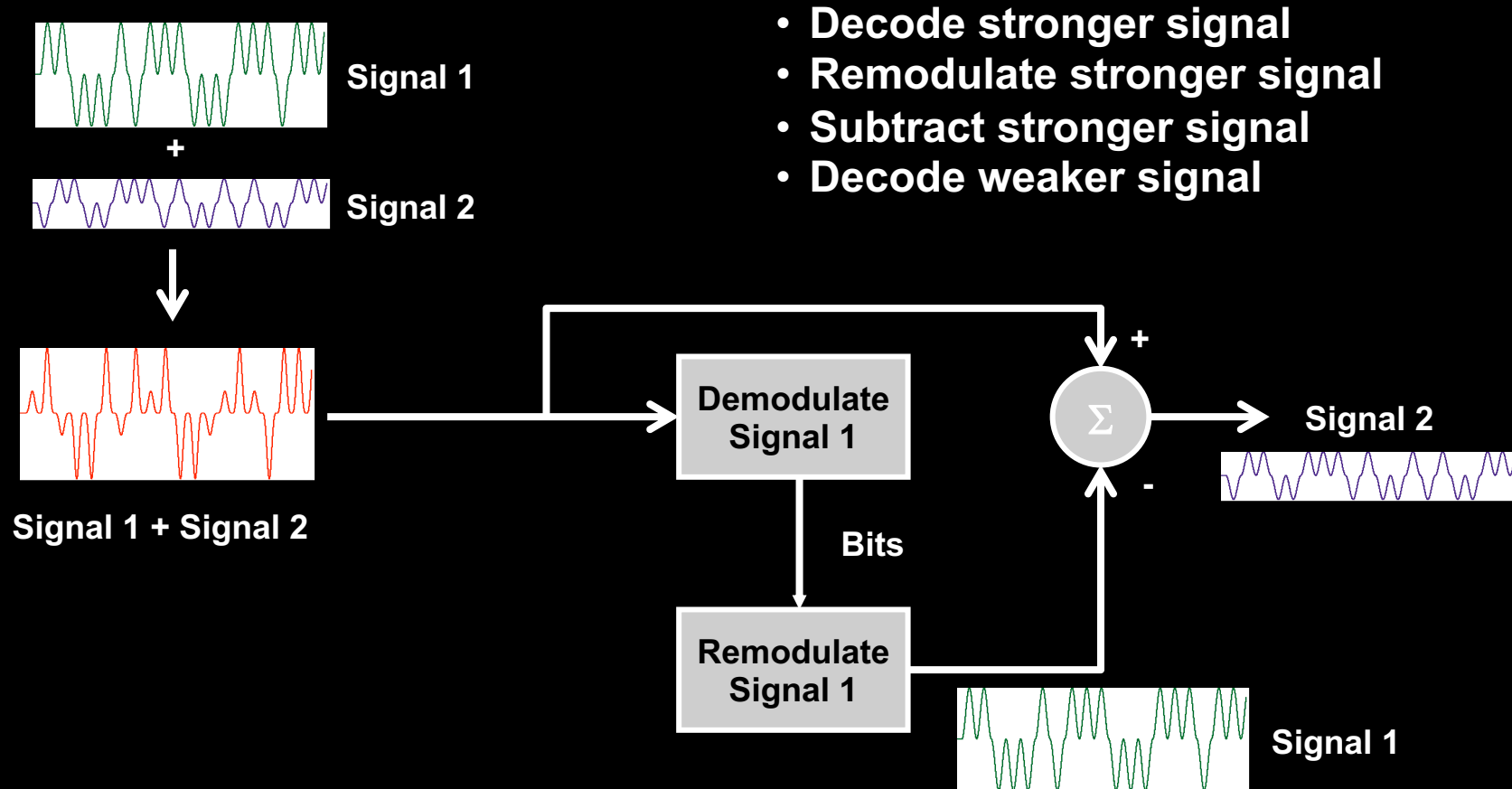
$$n_{\text{int}+n} = \sqrt{P_{\text{radar}}} \left(\sum_{m=1}^N a_m \frac{\partial s_{\text{radar}}(t - \tau_m)}{\partial t} n_{\tau,\text{proc}} \right) + n(t)$$

By Parseval's
Theorem

$$\sigma_{\text{int}+n}^2 = \langle \|n_{\text{int}+n}\|^2 \rangle$$



Simple Successive Interference Cancellation (SIC)



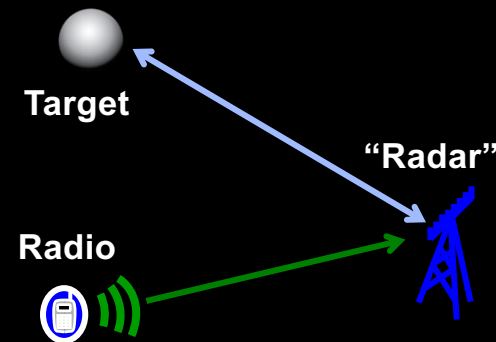
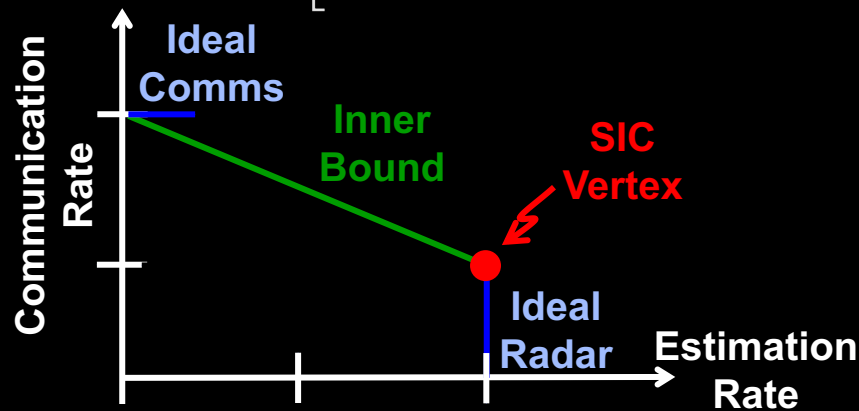
Evaluate SIC Point

- Find maximum communications rate such that the receiver can decode and subtract it in presence of radar return residual

$$R_{\text{com}} \leq B \log_2 \left[1 + \frac{b^2 P_{\text{com}}}{\sigma_{\text{int+n}}^2} \right] = B \log_2 \left[1 + \frac{b^2 P_{\text{com}}}{\|a\|^2 P_{\text{rad}} \gamma^2 B^2 \sigma_{\text{proc}}^2 + k_B T_{\text{temp}} B} \right]$$

- Then have ideal radar range estimation

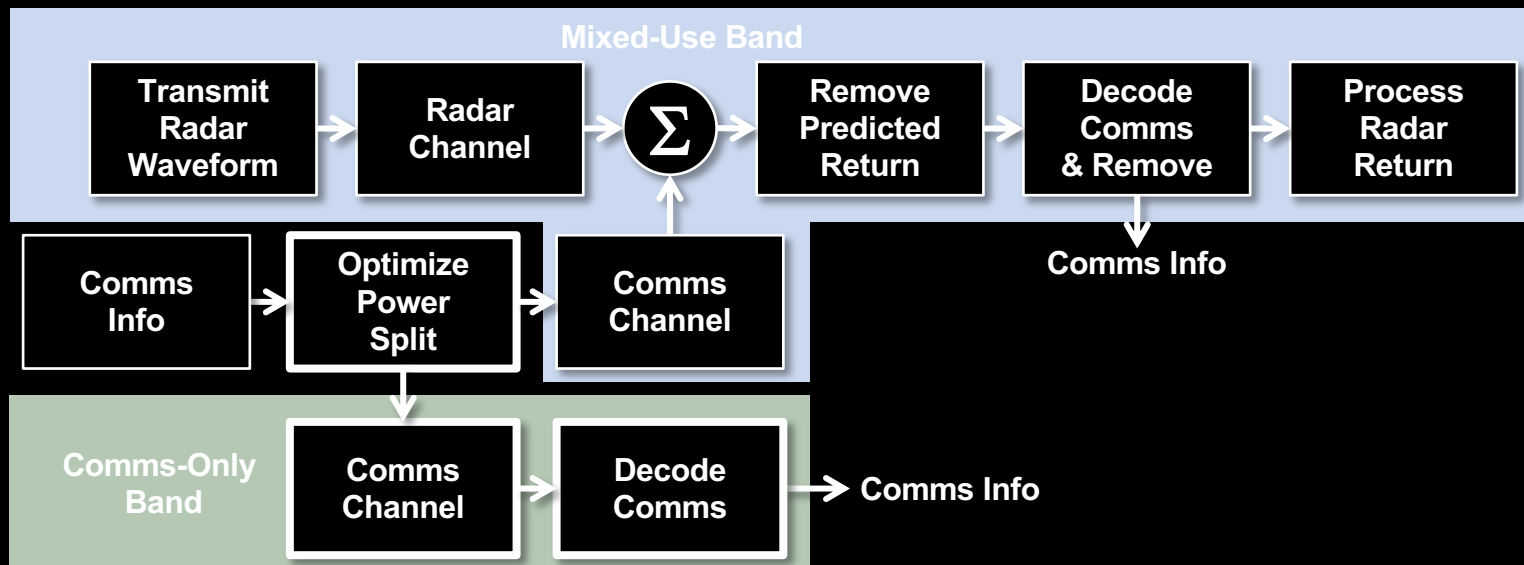
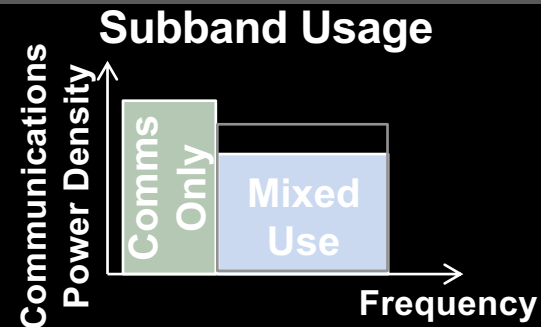
$$R_{\text{est}} \leq B \log_2 \left[1 + \frac{2\sigma_{\tau,\text{proc}}^2 \gamma^2 B (TB) \|a_m\|^2 P_{\text{rad}}}{k_B T_{\text{temp}}} \right]^{\delta/(TB)}$$



Bound Approach Overview

Water-Filling Joint Waveform Design

- Split into two sub-bands
 - Communications only
 - Mixed use
- Optimize communications power use by employing water-filling



Distribute Power By “Water-Filling”

- Optimize communications power/rate between bands
 - Operate mixed-use band at SIC point

$$B = B_{\text{com}} + B_{\text{mix}}$$

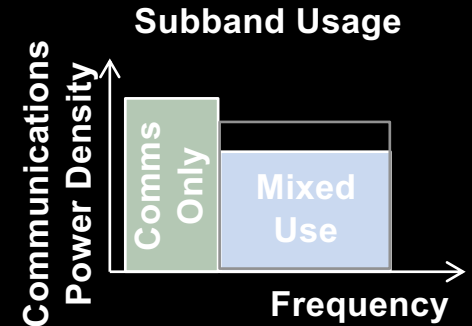
$$B_{\text{com}} = \alpha B$$

$$B_{\text{mix}} = (1 - \alpha) B$$

$$P_{\text{com}} = P_{\text{com,com}} + P_{\text{com,mix}}$$

$$P_{\text{com,com}} = \beta P_{\text{com}}$$

$$P_{\text{com,mix}} = (1 - \beta) P_{\text{com}}$$



- Define two channels

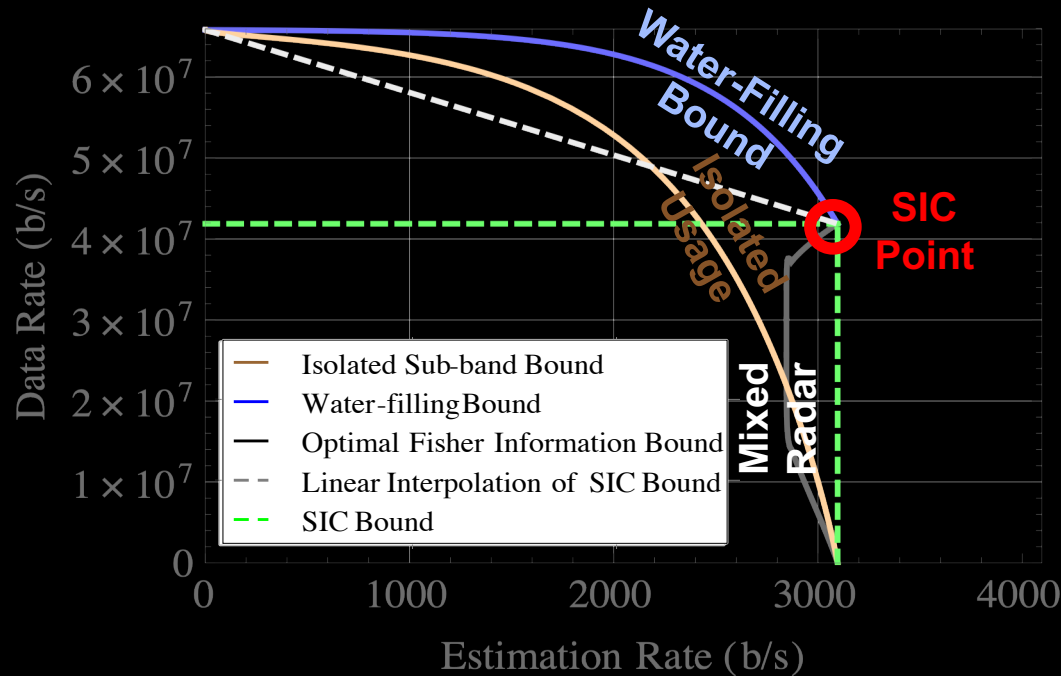
$$\mu_{\text{mix}} = \frac{b^2}{\sigma_{\text{int+n}}^2} \quad \mu_{\text{com}} = \frac{b^2}{k_B T_{\text{temp}} B_{\text{com}}}$$

- Optimal power distribution

$$\beta = \frac{P_{\text{com,com}}}{P_{\text{com}}} = \alpha + \frac{1}{P_{\text{com}}} \left(\frac{\alpha - 1}{\mu_{\text{com}}} + \frac{\alpha}{\mu_{\text{mix}}} \right) \quad \text{when } P_{\text{com}} \geq \frac{\alpha}{(1 - \alpha) \mu_{\text{mix}}} - \frac{1}{\mu_{\text{com}}}$$

Comparison of a Few Cooperative Operation Bounds

- Compare inner bounds
- Bounded by water-filling approach currently
 - Although its not tight



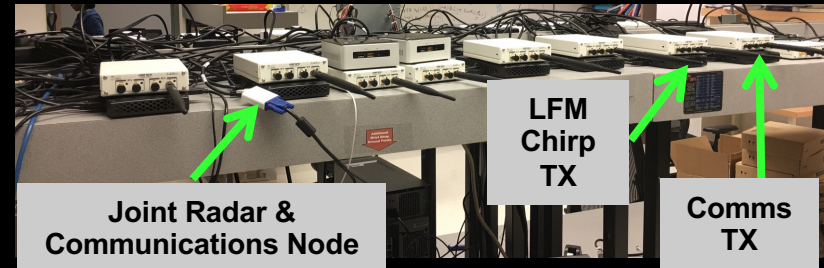
Parameter	Value
Bandwidth	5 MHz
Center Frequency	3 GHz
Temperature	1000 K
Communications Range	10 km
Communications Power	100 W
Communications Antenna Gain	0 dBi
Communications Receiver Side-lobe Gain	10 dBi
Radar Target Range	100 km
Radar Antenna Gain	30 dBi
Radar Power	100 kW
Target Cross Section	10 m^2
Target Process Standard Deviation	100 m
Time-Bandwidth Product	100
Radar Duty Factor	0.01

Joint Radar-Communications System

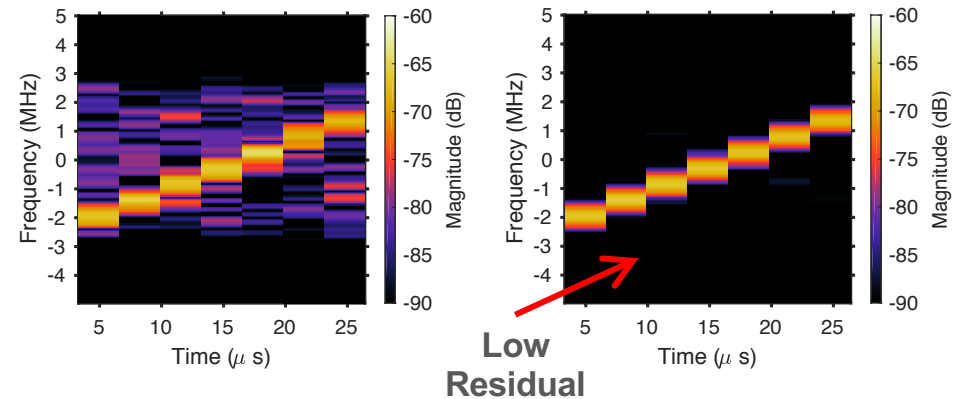
MATLAB-in-the-Loop Experiments

- **Demonstrate feasibility of joint radar-communications system**
 - Use dynamic network of software defined radios
 - Chirp and QPSK waveforms
 - Intelligent power and rate control between systems
- **Decode communications**
- **Remove communications**
- **Observe chirp with little communications residual**

Laboratory Setup



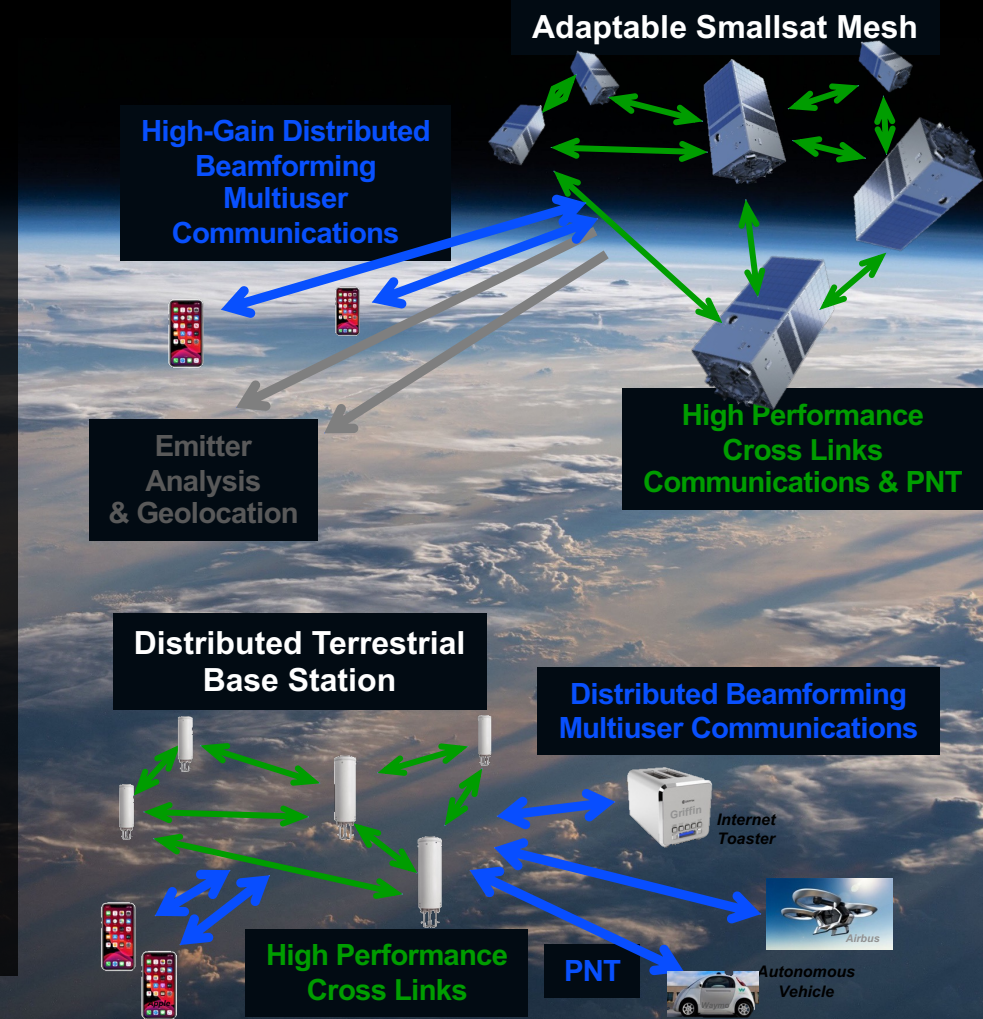
Performance Evaluation



Advanced Reconfigurable Systems

DC to Daylight

- Reinvent spectral employment by co-design of multi-function system
 - Provide transparent interface to spectrum
 - Higher data rate, better sensing, improved resilience
- Enable RF convergence
 - New functionalities
 - Multi-function systems
 - Communications, radar, PNT, etc...
- Enable flexible distributed carrier phase-coherent systems
 - Distributed wireless antenna arrays
- Integrate proliferated low C-SWaP space
- Develop advanced flexible systems
 - Bandwidth, power-scaling, dynamic range, ...
 - Flexible RF and optical
 - Flexible computations

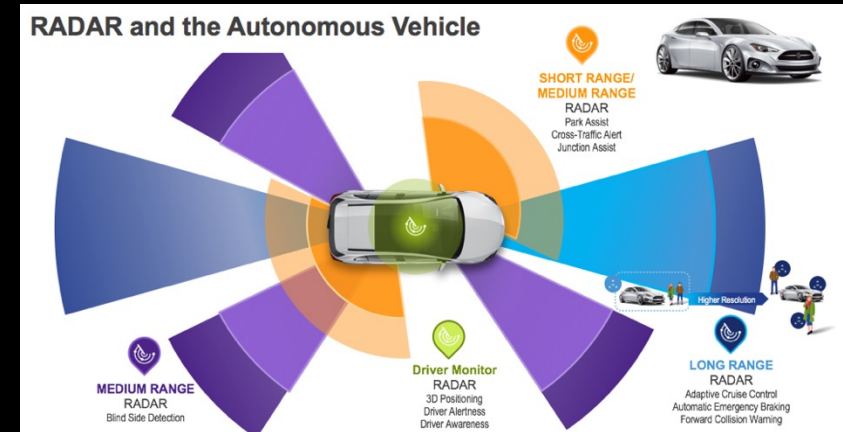


Backup

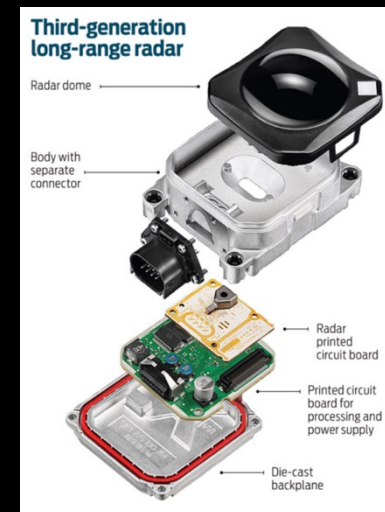


Automotive Radars

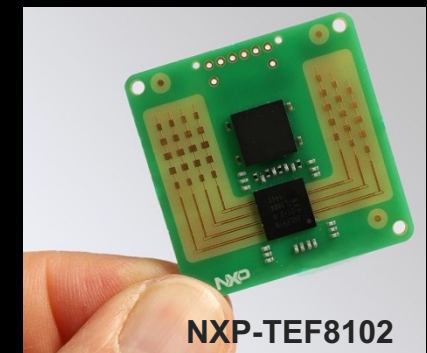
- Provide vehicle situational awareness
- Accepted broadly
 - New safety requirement
 - Mass production
- Drive system lower costs
 - Short and “long” range automotive radars ~ \$100
 - 24 GHz and 77 GHz
- Need improved system integration and functionality



<https://semiengineering.com/here-comes-high-res-car-radar/>



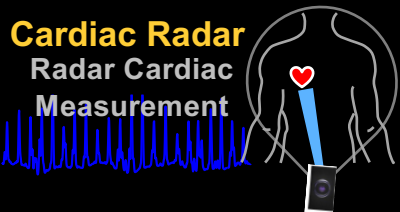
<https://spectrum.ieee.org/transportation/advanced-cars/longdistance-car-radar>



WISCA Projects

Wireless Information Systems and Computational Architectures Center

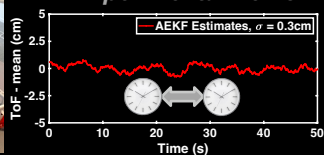
- Executing on a wide range of projects, large and small
- Developed strong relationships with industry and DoD sponsors



Advanced Positioning, Navigation, and Timing



Custom MIMO SDR, Novel Algorithms, Experimental Demo

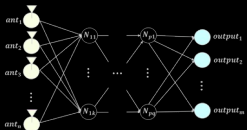


Next Generation Signal Processing And Machine Learning

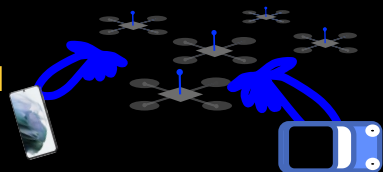
$$\mathbf{Z} \in \mathbb{C}^{(N_{ant} \times N_{tap}) \times N_{samp}}$$

$$\mathbf{w} = \frac{(\mathbf{Z}\mathbf{Z}^H)^{-1} \mathbf{Z}\mathbf{s}_m^H}{\mathbf{C}} \in \mathbb{C}^{(N_{ant} \times N_{tap}) \times 1}$$

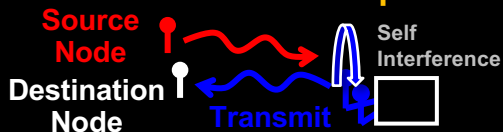
$$\hat{\mathbf{C}} = \mathbf{C}^{-1} \hat{\mathbf{v}}_m$$



Coherent Distributed Systems



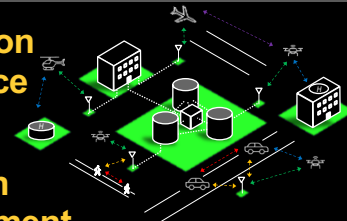
In-Band Full Duplex



Recent Funding

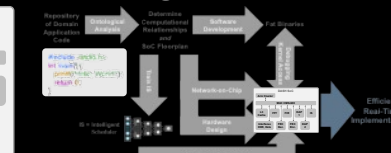
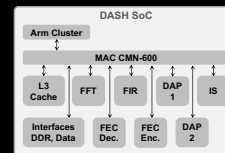


Multiple-Function RF Convergence

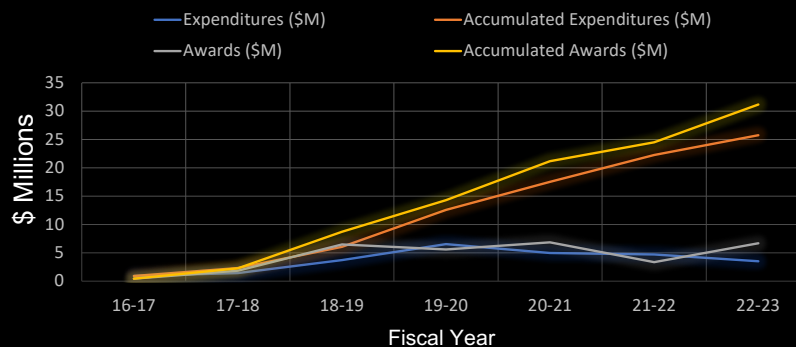


Next Generation Processor Development

Heterogeneous Processors Integrated Framework



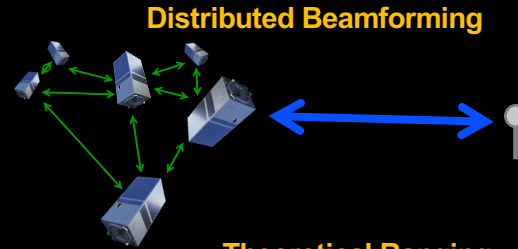
WISCA Awards and Expenditures



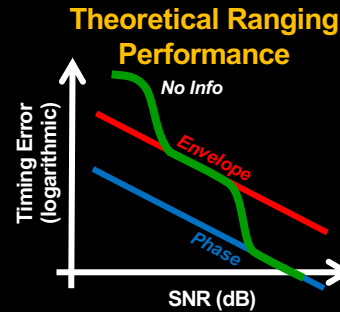
Carrier Phase-Accurate Positioning, Navigation, and Timing

Enabling Distributed Beamforming Technology

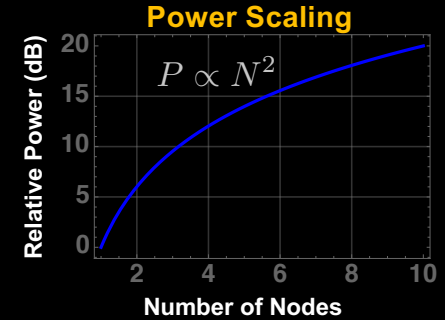
- Enable distributed capabilities with distributed coherence
 - Dramatically improve gain, $P \sim N^2$
 - Null interference and jamming
- Exploit carrier phase-accurate timing exchange approaches for PNT
 - Joint communications & PNT
 - Natural spoof resistance
- Employ our advances in MIMO carrier phase-coherent timing exchanges
 - Achieve 0.01m rather than 30m error



Distributed Beamforming



Theoretical Ranging Performance

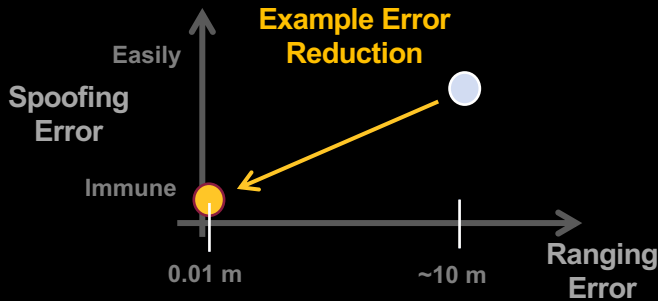


Power Scaling

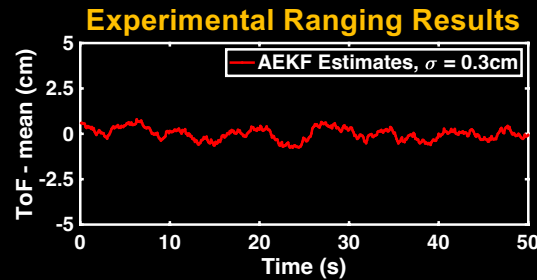


Distributed Coherence

ASU for Airbus System



Example Error Reduction



Experimental Ranging Results

Backup

