

Direction of Arrival Estimation (DOA) with MIMO Radar with Compressive Illumination

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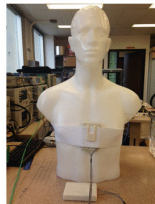
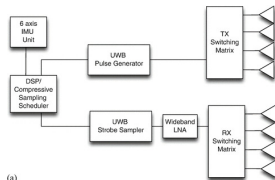
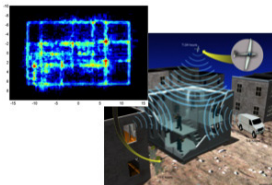
Specialists Meeting on Compressive Sensing applications for
Radar/ESM and EO/IR imaging

Outline

- 1 Wideband Multichannel Radar
 - Motivation
- 2 MIMO Radar
 - Problem and current approaches
 - Proposed solution
 - Problem statement
 - Simulation results
 - Hardware implementation

Wideband multichannel radar-Emerging applications

- Networked Sensing
- 3D/4D Imaging with Real Aperture Radar
- Massive MIMO



High Resolution radar imaging

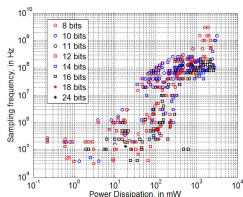
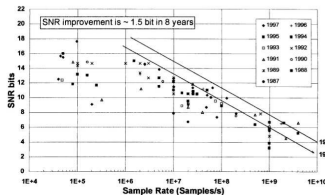
To achieve high resolution in range-angle of arrival domain, we need

- large illumination bandwidth leads to finer range resolution $\Delta_R = \frac{c}{2B}$.
- increase in transmitter and receiver systems lead to finer angle of arrival resolution $\Delta_{\cos(\theta)} = \frac{2}{N_T N_R}$

Wideband Radar Technology

Applications stretch the resolution and bandwidth capabilities of ADC technology

- COTS ADCs have limited resolution at high sampling rates
- Power consumption quadruples for additional bit of resolution [Wal99]



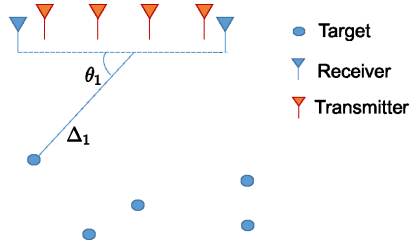
- Sample with available technology use signal recovery methods for high resolution
- Radar sensing is not just receive processing:
Illumination + Receiver Filtering + Sampling
- Challenge: Design transmit waveforms and receive filtering to shift burden away from ADC

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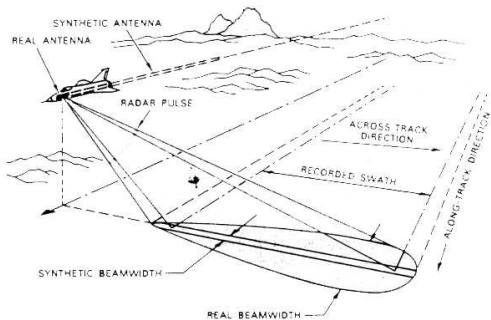
Problem

- We consider colocated multiple transmitters and receivers with a common reference.
- **Goal:** Estimate the round-trip delay Δ_i , angle of arrival θ_i , and target reflectivity x_i .
- **Approach:** Utilize compressive measurements from an incoherent domain.



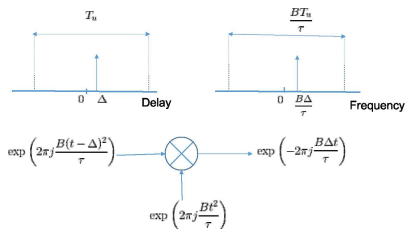
Before CS there was Stretch

- Stretch processing considers a fixed range swath.
- Uses LFM waveform on transmit and down-conversion implementing approximate match filtering.
- Converts delay estimation to tone estimation.



Stretch Processing with Chirp waveform

- Stretch processing considers a fixed range swath.
- Converts delay estimation to spectrum estimation.
- Sampling rate reduced from $B \rightarrow B \frac{T_u}{\tau}$



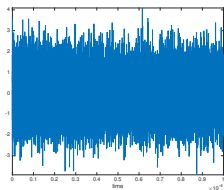
Can we design illumination schemes that further reduces sampling rate to exploit sparsity in scene?

Stochastic waveforms

Samples from a Sub-Gaussian distribution used as Tx waveforms [SNR15]¹ with good theoretical guarantees [KMR14]².

Issues

- Memory requirements
- Additional reference channel
- Power amplifier requirements due to high $PAPR = 20 \log_{10} \left(\frac{|x_{max}|}{x_{rms}} \right) \approx 15dB$.



¹M. Shastry, R. Narayanan, and M. Rangaswamy, *Sparsity-based signal processing for noise radar imaging*, IEEE Transactions on Aerospace and Electronic Systems, 2015

²Felix Kraemer, Shahar Mendelson, and Holger Rauhut, *Suprema of chaos processes and the restricted isometry property*, Communications on Pure and Applied Mathematics, 2014.

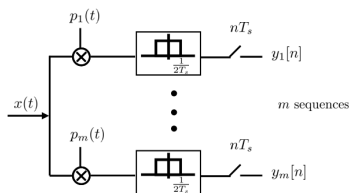
Modulated wideband converter based systems

Transmitted waveforms: Gaussian pulse[BIE14]³, FDMA and CDMA[CCEH16]⁴.

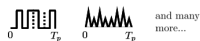
The periodic waveforms produce a mixed version of Fourier coefficients[GTE11]⁵

Issues

- Multichannel
- Sensitivity to crystal filter response
- Parallel channels with filtering and ADC required



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



⁴O. Bar-Ilan and Y. C. Eldar, *Sub-nyquist radar via doppler focusing*, IEEE Transactions on Signal Processing ,2014

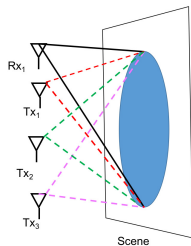
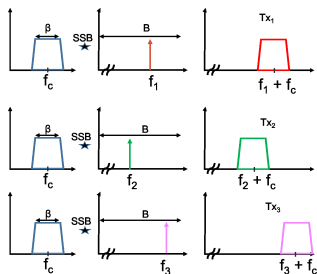
⁵David Cohen, Deborah Cohen, Yonina C. Eldar, and Alexander M. Haimovich, *Summer: Sub-nyquist MIMO radar*,2016

⁶K. Gedalyahu, R. Tur, and Y. C. Eldar, *Multichannel sampling of pulse streams at the rate of innovation*, IEEE Transactions on Signal Processing 2011

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Proposed approach - Multi-frequency modulated waveform

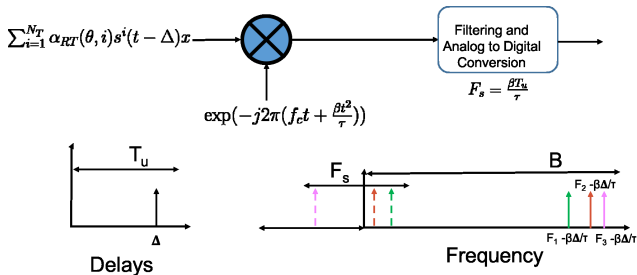


Transmitted waveform at Tx i: $s^i(t) = \exp\left(2\pi j\left(f_c t + \frac{\beta}{2T} t^2\right)\right) \times s_i(t)$

$$s_i(t) = \frac{1}{\sqrt{N_c N_T}} \sum_k^{N_c} \exp(2\pi j f_i(k) t).$$

Received Signal

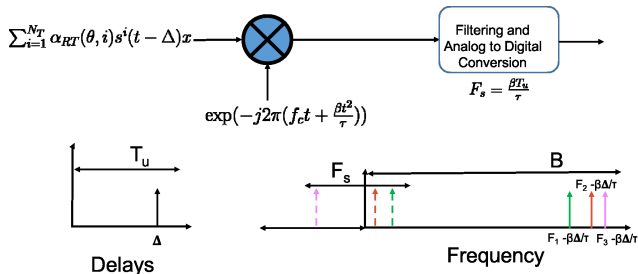
Stretch processor samples at receiver



$$y(n) = \sum_{k=1}^{N_{Targets}} \sum_{i=1}^{N_T} \sum_{c=1}^{N_c} x_k \alpha_{RT}(\theta_k, i) \exp\left(2\pi j \left(f_i(c) - \frac{\beta \Delta_k}{\tau}\right) \frac{n}{F_s}\right) \times \exp(2\pi j f_i(c) \Delta_k) + w(n)$$

Received Signal

Stretch processor samples at receiver



Stretch Processing: Range $x \Rightarrow$ Tone Estimation

MultiFrequency LFM: Range \Rightarrow Structured Line Spectrum Estimation

Discussion

Advantages

- MIMO architecture with undersampling in spatial and delay domains
- $PAPR \approx 3 + 10 \log(N_c)$ dB to 1!
- Standard calibration procedures

Drawbacks

- Large analog bandwidth required for ADC
- Computational Complexity of Recovery

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Problem Definition

Given a scene with small number of targets $N_{Targets}$, we define

$$\mathbf{y} = \int_{\Delta, \theta} \Psi(\Delta, \theta) d\mu + \mathbf{w}.$$

$$\Psi(n, \Delta, \theta) = \sum_{i,c} \alpha_{RT}(\theta, i) \exp\left(2\pi j \left(f_i(c) - \frac{\beta\Delta}{\tau}\right) \frac{n}{F_s}\right) \exp(2\pi j f_i(c)\Delta)$$

$$\mu = \sum_{k=1} x_k \delta(\Delta - \Delta_k, \theta - \theta_k).$$

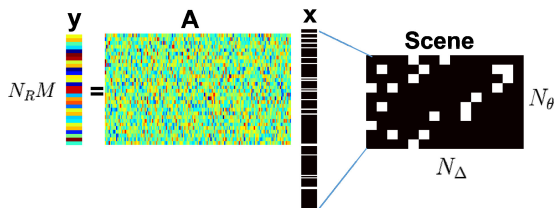
We estimate the angle of arrival θ and delay Δ by solving

$$\min_{\mu} \left\| \mathbf{y} - \int_{\Delta, \theta} \Psi(\Delta, \theta) d\mu \right\| \quad \text{Subject to } \|\mu\|_{TV} \leq \tau, \quad (1)$$

$$\text{where, } \|\mu\|_{TV} = \sum_k |x_k|.$$

Discretization approach

- Range space is discretized with resolution $\Delta_R = \frac{c}{2B}$.
- The non-linear mapping $\cos(\theta)$ of the angle of arrival is discretized with resolution $\Delta_\theta = \frac{1}{N_T N_R}$.



$$\min_{\mathbf{x}} \|\mathbf{x}\|_1 \quad \text{Subject to} \quad \|\mathbf{A}\mathbf{x} - \mathbf{y}\|_2 \leq \|\mathbf{w}\|_2.$$

Recovery Guarantees (Single TX/ RX))

Matrix Type of size $M \times N$	Mutual Coherence	Spectral Norm	Sparsity for successful recovery	Minimum signal strength	Reference
Random matrix with independent random entries (NM)	$2\sqrt{\frac{\log N}{M}}$	$\sqrt{\frac{N}{M}} + 1$	$\mathcal{O}\left(\frac{M}{\log N}\right)$	$\mathcal{O}(\sigma\sqrt{2\log N})$	[CJ11, CP09, DS01]
Toeplitz block matrix with $(N + M)$ random entries	$\mathcal{O}\left(\sqrt{\frac{\log N}{M}}\right)$	$\mathcal{O}\left(\sqrt{\frac{N}{M}}\right)$	$\mathcal{O}\left(\frac{M}{\log N}\right)$	$\mathcal{O}(\sigma\sqrt{2\log N})$	[Baj12]
LFM waveform modulated with $N_c \ll N$ randomly selected tones for single transmitter and receiver	$\mathcal{O}\left(\sqrt{\frac{\log N}{M}}\right)$	$\mathcal{O}\left(2\sqrt{\frac{N \log(N+M)}{M}}\right)$	$\mathcal{O}\left(\frac{M}{\log N \log(N+M)}\right)$	$\mathcal{O}(\sigma\sqrt{2\log N})$	[SE15, SE16]

Recovery Guarantees (MIMO)

Matrix Type of size $N_R M \times N_\Delta N_\theta$	Sparsity for successful recovery	Minimum signal strength	Reference
Toeplitz block matrix with $(N_T M + N_\Delta)$ random entries	$\mathcal{O}\left(\frac{N_R M}{\log(N_\Delta N_\theta)}\right)$	$\mathcal{O}\left(\sigma \sqrt{2 \log(N_\Delta N_\theta)}\right)$	[Baj12] ⁶
LFM waveform modulated with $N_c \ll \frac{N_\Delta}{N_T}$ randomly selected tones per transmitter	$\mathcal{O}\left(\frac{N_R M}{\log^2(2N_\Delta N_\theta)}\right)$	$\mathcal{O}\left(\sigma \sqrt{2 \log(N_\Delta N_\theta)}\right)$	This work

⁷Waheed Bajwa, *Geometry of random toeplitz-block sensing matrices: bounds and implications for sparse signal processing*, Proc. SPIE ,2012

Continuous Domain solution

We solve the following problem

$$\min_{\mu} \left\| \mathbf{y} - \int_{\Delta, \theta} \Psi(\Delta, \theta) d\mu \right\| \quad \text{Subject to } \|\mu\|_{TV} \leq \tau, \quad (2)$$

where, $\|\mu\|_{TV} = \sum_k |x_k|$.

We exploit the differentiability of $\Psi(\Delta, \theta)$ in the parameters to refine the support [BSR17]⁷.

⁸Nicholas Boyd, Geoffrey Schiebinger, and Benjamin Recht, *The alternating descent conditional gradient method for sparse inverse problems*, SIAM Journal on Optimization, 2017.

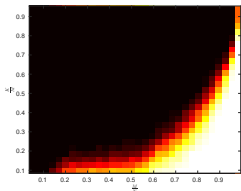
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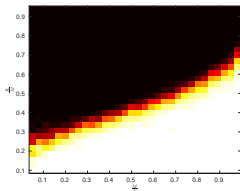
On-Grid results - Noiseless recovery

Single Tx-Rx system

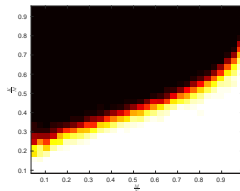
Performance criterion - $P(MSE < 1e-5)$



1 Tone



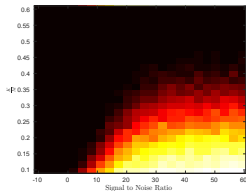
10 tones modulation



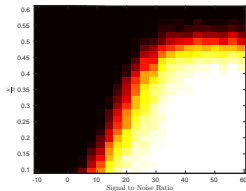
Gaussian waveform

On-Grid results - Noisy support recovery

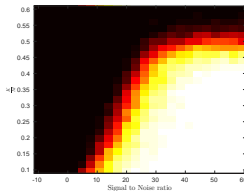
Single Tx-Rx system with $\beta/B = 0.5$
 Performance criterion - $P(AUC > 0.99)$



1 Tone



10 tones modulation



Gaussian waveform

Off-grid recovery DOA- Performance metrics

We use performance metrics defined in [TBR15]⁸

Given estimated model $\sum_j \hat{x}_j \Psi(\hat{\Delta}_j)$ and true model $\sum_{i=1}^K x_i \Psi(\Delta_i)$

$\mathcal{T} = \{\Delta_j\}$ set of true parameters

$N_{\Delta_j} = \{\Delta \in \Omega : \|\Delta - \Delta_j\| \leq 0.2c/(2B)\}$

$\mathcal{F} = \Omega \setminus \mathcal{T}$

- error due to false detections given by $m_1 = \sum_{\hat{\Delta}_i \in \mathcal{F}} |\hat{x}_i|$,
- weighted localization error $m_2 = \sum_j \sum_{i: \hat{\Delta}_i \in N_{\Delta_j}} |\hat{x}_i| \min_{\Delta \in \mathcal{T}} \|\hat{\Delta}_i - \Delta\|^2$,
- approximation error in the scattering coefficients

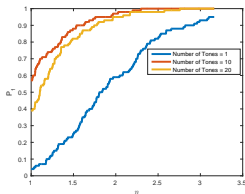
$$m_3 = \sum_{\Delta_j \in \mathcal{T}} \left| x_j - \sum_{\hat{\Delta}_l \in N_{\Delta_j}} \hat{x}_l \right|.$$

⁸Gongguo Tang, B.N. Bhaskar, and B. Recht, *Near minimax line spectral estimation*, IEEE Transactions on Information Theory, 2015.

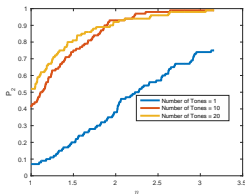
Performance comparison

Performance profile

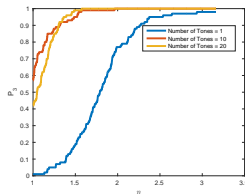
$$P_s(\eta; i) = \frac{\text{card} \{p \in \mathcal{P} : m_i(p, s) \leq \eta \min_s m_i(p, s)\}}{\text{card} \{\mathcal{P}\}}. \quad (3)$$



False detections



Localization error

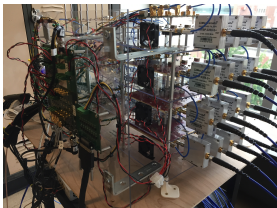


Approximation error

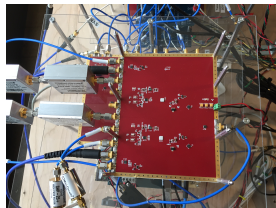
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Hardware setup

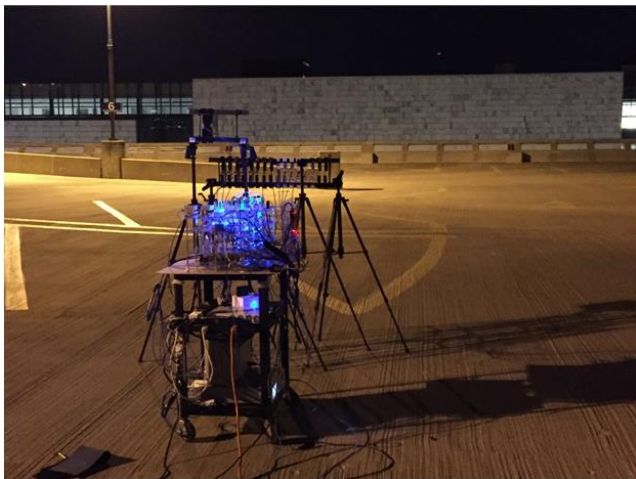


DDS Transmitter -32



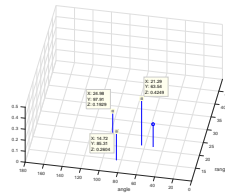
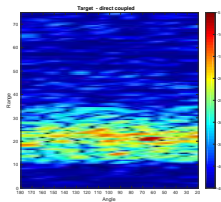
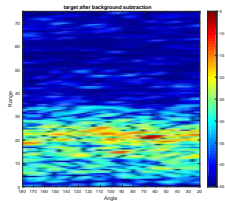
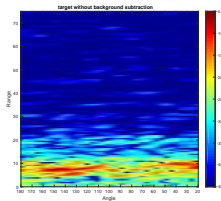
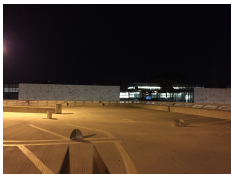
Stretch Receiver

Hardware setup- TX, RX and antenna array



Experiment

Setup



Summary and Future Work

MIMO Radar

- Extended compressive illumination scheme to MIMO radar and spatial processing
- Established theoretical guarantees for the sampling rate requirements as a function of the sparsity of the scene.
- Simulated and Measured Data Experiments reveal accurate recovery of spars scenes.

Future Work

- Calibration for phase mismatches between channels. Key observation: Unlike classical beamformers range and spatial processing is coupled.

References I



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References II



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R. H. Walden, *Analog-to-digital converter survey and analysis*, IEEE Journal on Selected Areas in Communications **17** (1999), no. 4, 539–550.

Parameter choice

Parameter	Value
Bandwidth B	$500 \times 10^6 \text{ Hz}$
Range Interval	$[0, 100] \text{ m}$
Number of Range Bins N	334
Unambiguous time interval t_u	$6.6 \times 10^{-7} \text{ s}$
pulse duration τ	$6.86 \times 10^{-5} \text{ s}$