Sparse Signal Processing Techniques for Electromagnetic Applications

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EPSRC "Low Power Mm-wave"

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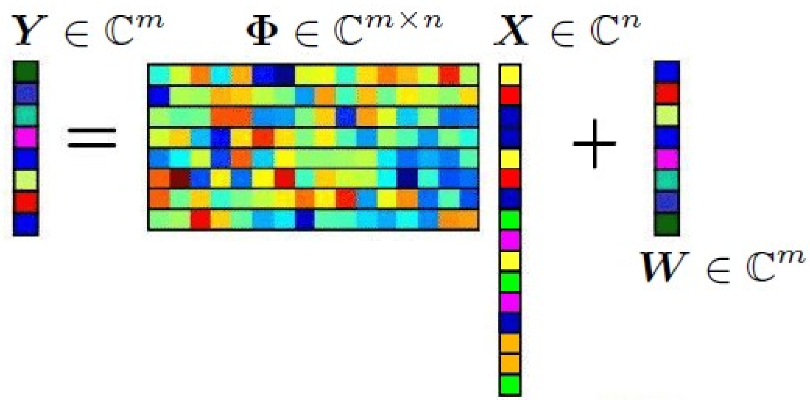
Sparse Signal Processing

- Sparse Signal Processing aims to reconstruct a signal $\mathbf{X}$ using as few samples of $\mathbf{Y}$ as possible, with the help of measurement matrix $\mathbf{\Phi}$

$$\boldsymbol{Y} = \boldsymbol{\Phi}\boldsymbol{X} + \boldsymbol{W}$$

$$m \ll n$$



- Subject area received a lot of attention with **Compressed Sensing (2006)**
- More recently, techniques have evolved to be used in many sensing problems
- Discuss two examples for **Mm-wave communications** and **Radar sensing**

Emmanuel Candès

David Donoho

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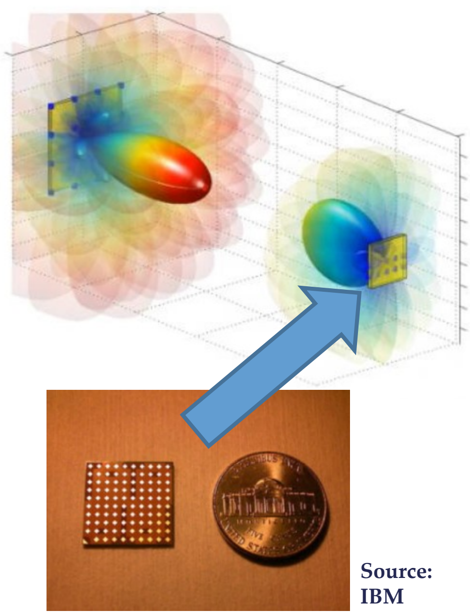
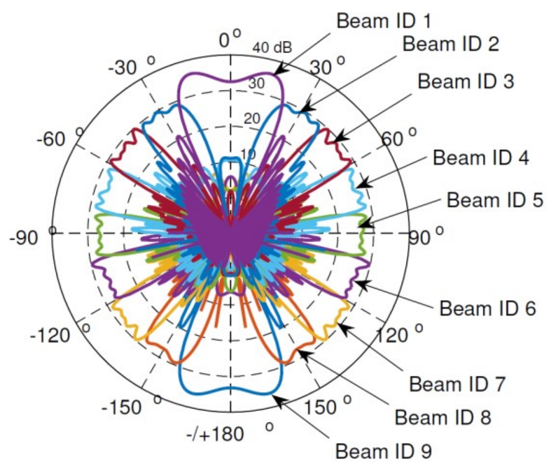
Part 1: Energy Efficient Mm-Wave Systems

- **Millimetre wave bands** provide higher capacity; use directional beamforming to mitigate channel effects
- First systems to launch operate around **24-28 GHz bands**
- How does **sparsity** play a role in mm-wave communications?
  - Number of multipath components is small
  - Aim to minimise energy consumption and activated hardware components: **Hybrid Architecture**



Source: IBM



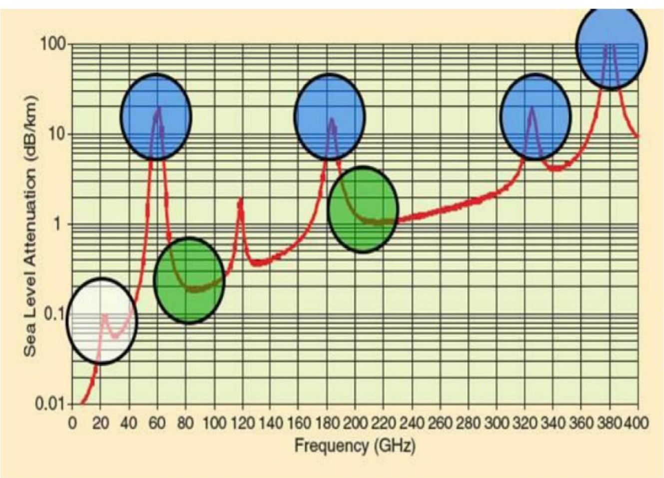


Figure 2 of T.S. Rappaport et al, IEEE Access, May 2013

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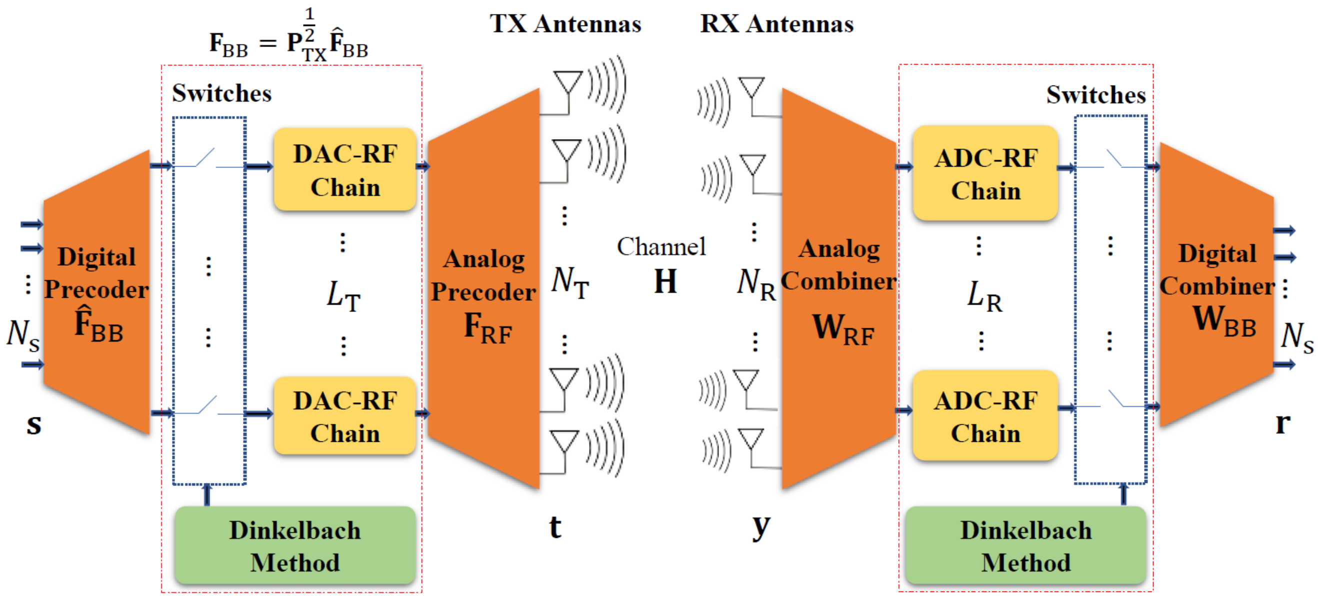
Source: P. Cao et. al., "Constant Modulus Shaped Beam Synthesis via Convex Relaxation," IEEE AWP Letters, pp. 617-620, 2017.

Hybrid mm-Wave Architecture



- Using Multiple TX/RX Antennas enables **Spatial Multiplexing**
- Nº TX Antennas N_T >> Nº of Spatial Streams N_S
- Minimise Nº of activated RF Chains L_T to improve **energy efficiency**

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Optimising Energy Efficiency

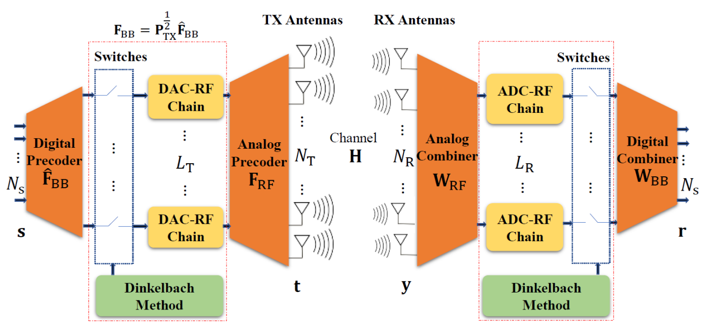
- Communications system has TX power levels $\mathbf{P}_{\text{TX}}$
- Given the **spectral efficiency** $R(\mathbf{P}_{\text{TX}})$
- And the TX/RX **power consumed** $P(\mathbf{P}_{\text{TX}})$
- The **Energy Efficiency** is defined by:

$$\boxed{\text{EE}(\mathbf{P}_{\text{TX}}) \triangleq \frac{R(\mathbf{P}_{\text{TX}})}{P(\mathbf{P}_{\text{TX}})} \quad \text{(bits/Hz/J).}}$$

- Usually have a minimum rate constraint on $R(\mathbf{P}_{\text{TX}})$

Difficult quantity to optimise:

Ratio of two complex functions



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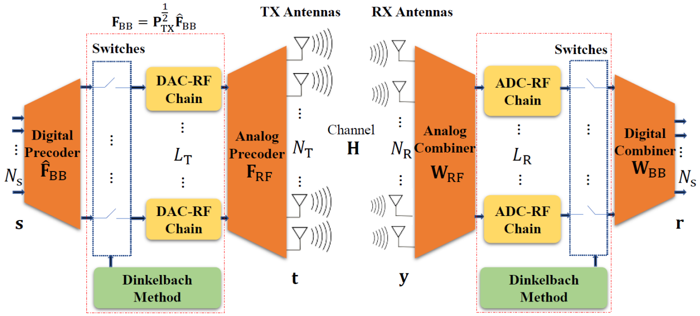
Power Consumption Modelling

- Interested in the **total power** *P* consumed by the transmit-receive system, not just the TX power $\mathbf{P}_{\mathrm{TX}}$
- Use a model that computes the power for each element of TX/RX, including circuit power consumption
- Assume TX power amplifier is 40% efficient
- Summing these terms gives total power consumed

Power Term	Value
Power required by all circuit components	$P_{\mathrm{CP}} = 10$ W
Power required by each RF chain	$P_{\mathrm{RF}} = 100$ mW
Power required by each phase shifter	$P_{\mathrm{PS}} = 10$ mW
Power per TX/RX antenna element	$P_{\mathrm{T}} = P_{\mathrm{R}} = 100$ mW
Maximum allocated power	$P_{\max} = 1$ W

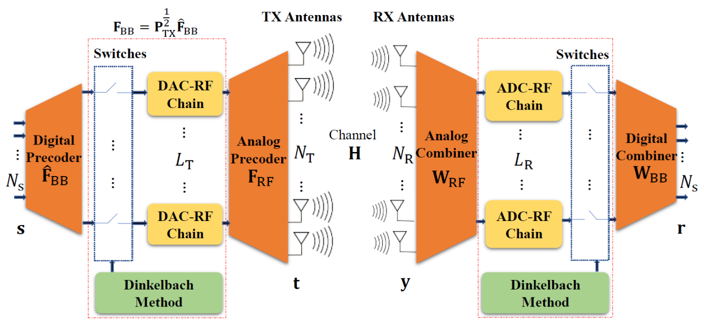


Example Power Consumption Settings for a mm-wave MIMO system

Brute Force Approach

- **Main Goal:** Find Nº of RF chains to maximise **EE**
- Basic Approach:
  - Measure the channel matrix **H**
  - Compute $R(\mathbf{P}_{\mathrm{TX}})$ and $P(\mathbf{P}_{\mathrm{TX}})$ for each possible number of RF chains
  - Find the number $L_{\mathrm{T}}^{\mathrm{opt}}$ that maximises **EE**
- This approach directly solves the problem

Method is complex as we have to design a complete receiver for each Choice of RF chains!



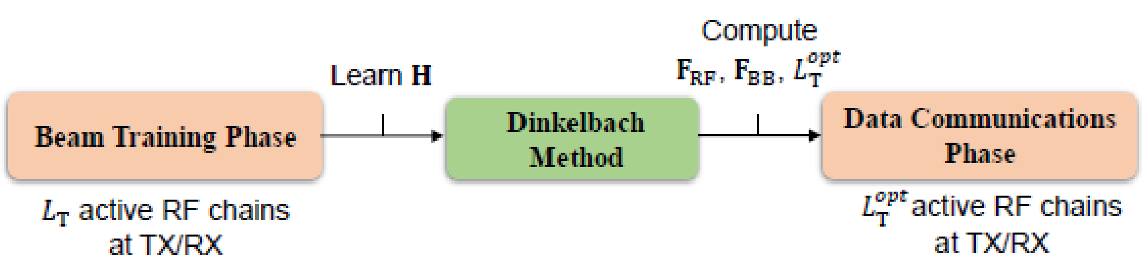
Source: R. Zi et al., "Energy efficiency optimization of 5G radio frequency chain systems", IEEE JSAC., Vol. 34(4), pp. 758-771, 2016

Dinkelbach Method

- First idea: Use approximation for rate $R(\mathbf{P}_{\mathrm{TX}})$
- Second idea: We adopt the Dinkelbach Method:

$$\boxed{\max_{\mathbf{P}^{(m)} \in \mathcal{D}^{L_{\mathrm{T}} \times L_{\mathrm{T}}}} \left\{ R(\mathbf{P}^{(m)}) - \nu^{(m)} P(\mathbf{P}^{(m)}) \right\}}$$

  - Used to optimize the ratio of two functions
  - Use several iterations to find the optimum number of RF chains $L_{\mathrm{T}}^{\mathrm{opt}}$ and value of **EE**
- Method much simpler than **Brute Force** but still yields good **Energy Efficient** solutions



Source: A. Kaushik et al., "Dynamic RF Chain Selection for Energy Efficient and Low Complexity Hybrid Beamforming in Millimeter Wave MIMO Systems" IEEE TGCN, Vol. 3(4), Dec. 2019.

Simulations

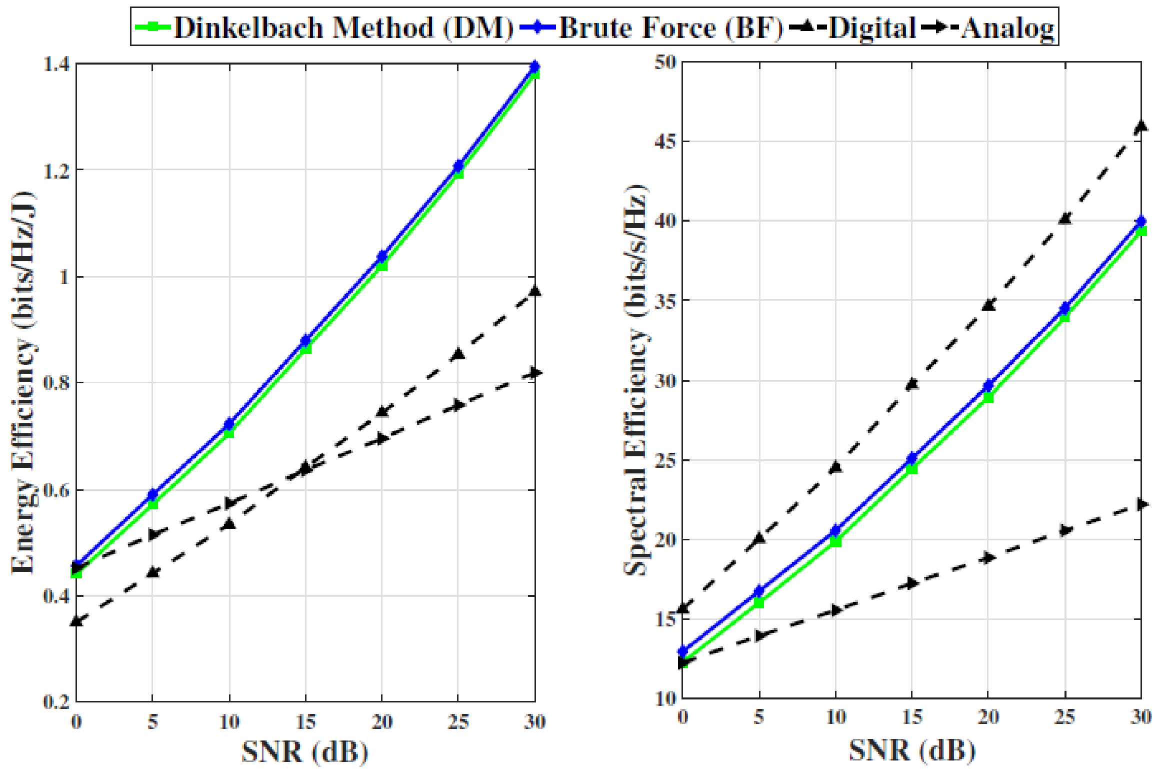
Simulated a single user MIMO system using 1000 Monte Carlo Runs with N_T=32 and N_R=8 antennas

System Parameter	Value
Number of clusters	$N_{\text{cl}} = 2$
Number of rays	$N_{\text{ray}} = 10$
Angular spread	$7.5°$
Average power for each cluster	$\sigma_{\alpha,i} = 1$
Mean angles (azimuth domain)	$60° - 120°$
Mean angles (elevation domain)	$80° - 100°$
Normalized system bandwidth	1 Hz
SNR	$1/\sigma_{\text{n}}^2$
Amplifier efficiency	$1/\beta = 0.4$
Minimum desired SE in (10)	$R_{\text{min}} = 1$ bits/s/Hz
Tolerance values	$\epsilon = 10^{-4}$ and $\epsilon_{\text{th}} = 10^{-6}$
Number of available RF chains	$L_{\text{T}} = L_{\text{R}} = \text{length}(\text{eig}(\text{HH}^H))$
Spacing between antenna elements	$d = \lambda/2$ (e.g., $\lambda = 1/28$ GHz [13])

Systems Studied

1. **Brute Force**
2. **Dinkelbach**
3. **Analog** – 1 RF chain
4. **Digital** – One RF chain per antenna

Simulation Results/Observations

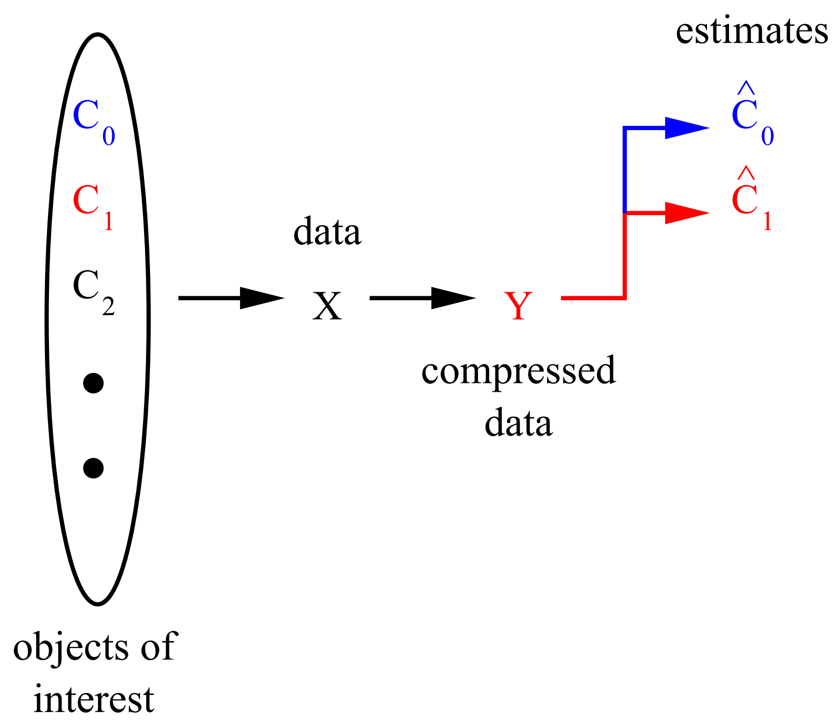


N_T=32 & N_R=8 antennas

Observations: Dinkelbach Method achieves similar EE to Brute Force method but lower SE than Digital;
Dinkelbach Method typically converges in 3 iterations

Part 2: Reconfigurable Signal Processing

- **UDRC WP2.2:** Signal processing systems routinely dispose of information in the processing chain
- This "lost" information may be worth recovering:
  - for rapid reconfiguration to address imminent threat;
  - in post-engagement forensic analysis.
- How does **sparsity** play a role:
  - Minimize storage needed for **Y**
  - Limits post-processing for estimation or classification

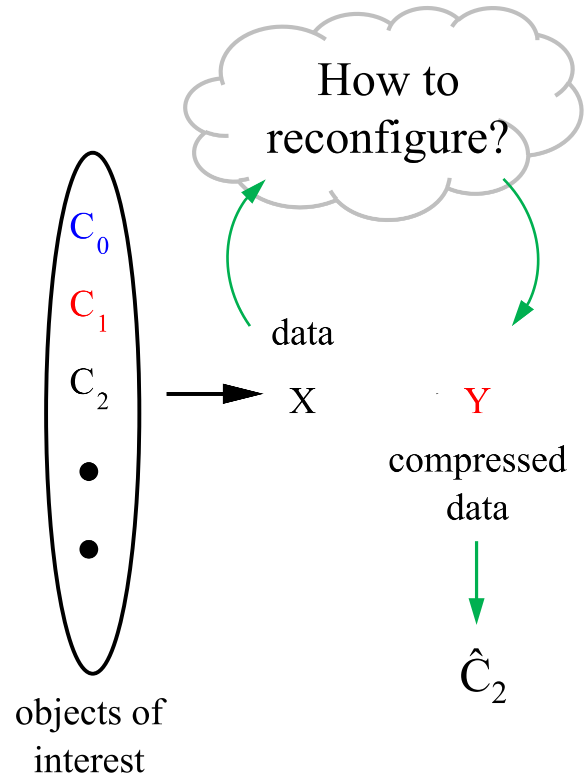


WP2.2: Research Questions & Challenges

What are:

- the fundamental limits of such information recovery;
- active steps that can be put in place to facilitate it;
- the algorithms to reconfigure the data flow to implement the necessary recovery?
- Typically operating in resource constrained scenarios

Demanding because it is not known *a priori* which "lost" information the operator will ask for.



Application to Micro-Doppler Signatures

- Model the received signals using stochastic **Gaussian mixture distributions**.
- Prior work has used real-valued magnitude data taken from time-frequency representations.
- Use **Complex-valued** framework to classify micro-Doppler (m-D) signatures with structured input noise.
- Potential to simultaneously detect the classes of:
  - a primary source exhibiting m-D features in its radar return;
  - a secondary, coincident source with its own m-D signature.
- Evaluations using real radar return data collected at Strathclyde University (Thanks to: **Dr Carmine Clemente, Domenico Gaglione & Christos Ilioudis**)

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New Information Theoretic Result

- For the micro-Doppler scenario our signal model is:

$$Y = \Phi(X + N) + W = \Phi Z + W \qquad C \rightarrow X \rightarrow Z \rightarrow Y$$

- Here **X** represents the information source of interest and **N** is the second/fleeting signal.
- In order to choose the best measurement matrix $\mathbf{\Phi}$, a new gradient function has been derived:

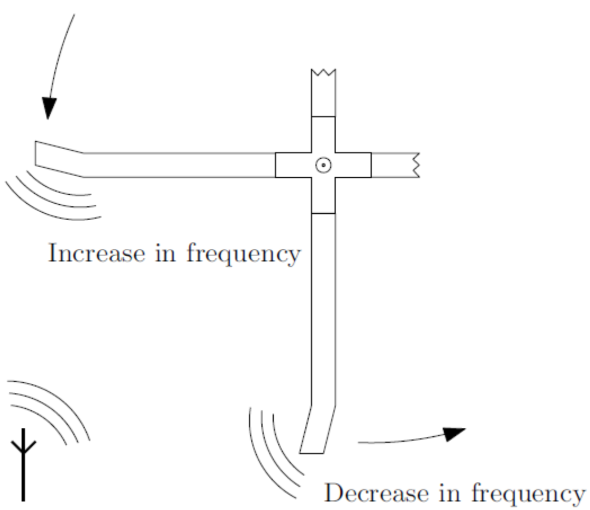
$$\nabla_{\mathbf{\Phi}} I(C; Y) = \mathbf{\Lambda}^{-1} \mathbf{\Phi} \mathbf{E}_{z,c} \,.$$

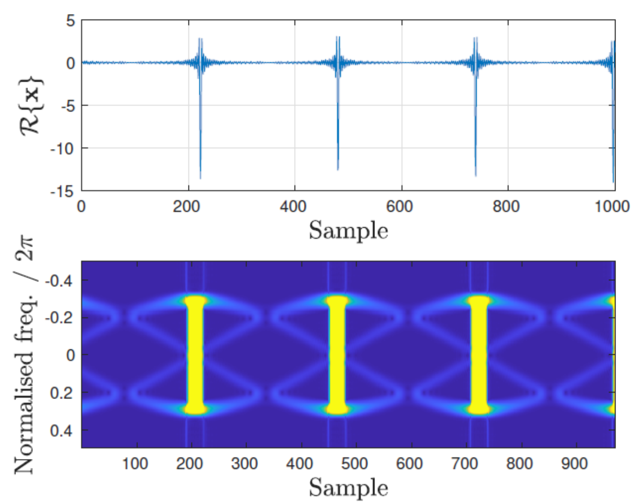
- The matrix $\mathbf{\Lambda}$ is the covariance matrix of the noise **W** and $\mathbf{E}_{z,c}$ is a mean squared error matrix for **Z**
- The gradient calculation is used to iteratively improve $\mathbf{\Phi}$ to optimise a given metric, e.g. **correct signal classification**

Source: F. Coutts et. al, "Information-Theoretic Compressive Measurement Design for Micro-Doppler Signatures", In Proc IEEE SSPD 2020 Conf.

Micro-Doppler Signature Example

- The main motion of an object with respect to a radar determines its predominant Doppler frequency shift.
- Any secondary motions, such as the rotation of an aircraft's rotor blades, contribute with features known as m-D signatures.
- E.G. **Apache Helicopter**, 4 blades of length 7.32m @ 289 rpm:





WP2.2: Generation of Radar Data

- UDRC Phase 2 dataset from Strathclyde comprises coincident radar returns from two sources.

- Our primary task is to classify the speed of the first fan.
- Can we make our measurement model flexible such that we can simultaneously detect the speed of the second fan?

Simulation Results

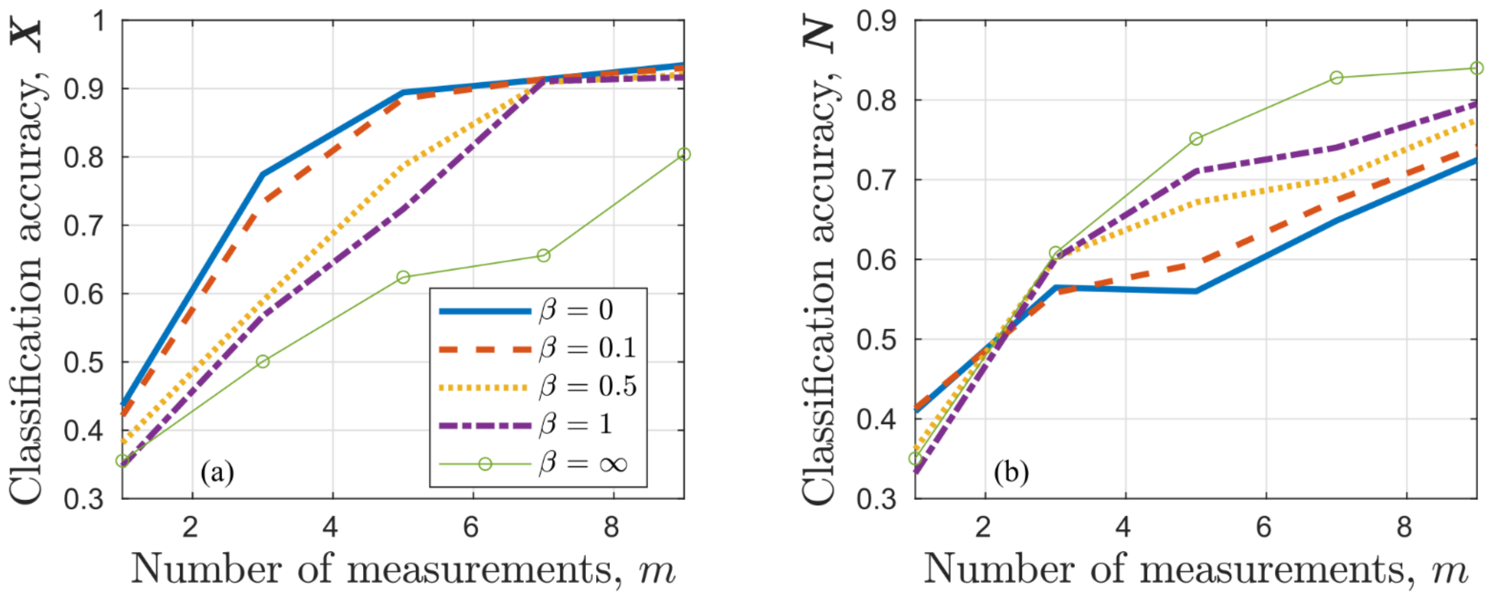
$$\boldsymbol{Y} = \boldsymbol{\Phi}(\boldsymbol{X} + \boldsymbol{N}) + \boldsymbol{W}$$

Additive Noise

Primary, always-present source with classes C

Secondary, fleeting source with classes L

Objective Function: $\max_{\boldsymbol{\Phi}} F(\boldsymbol{\Phi}, \beta) = \max_{\boldsymbol{\Phi}} \{ I(C; \boldsymbol{Y}) + \beta \cdot I(L; \boldsymbol{Y}) \}$ $\quad \beta \geq 0$



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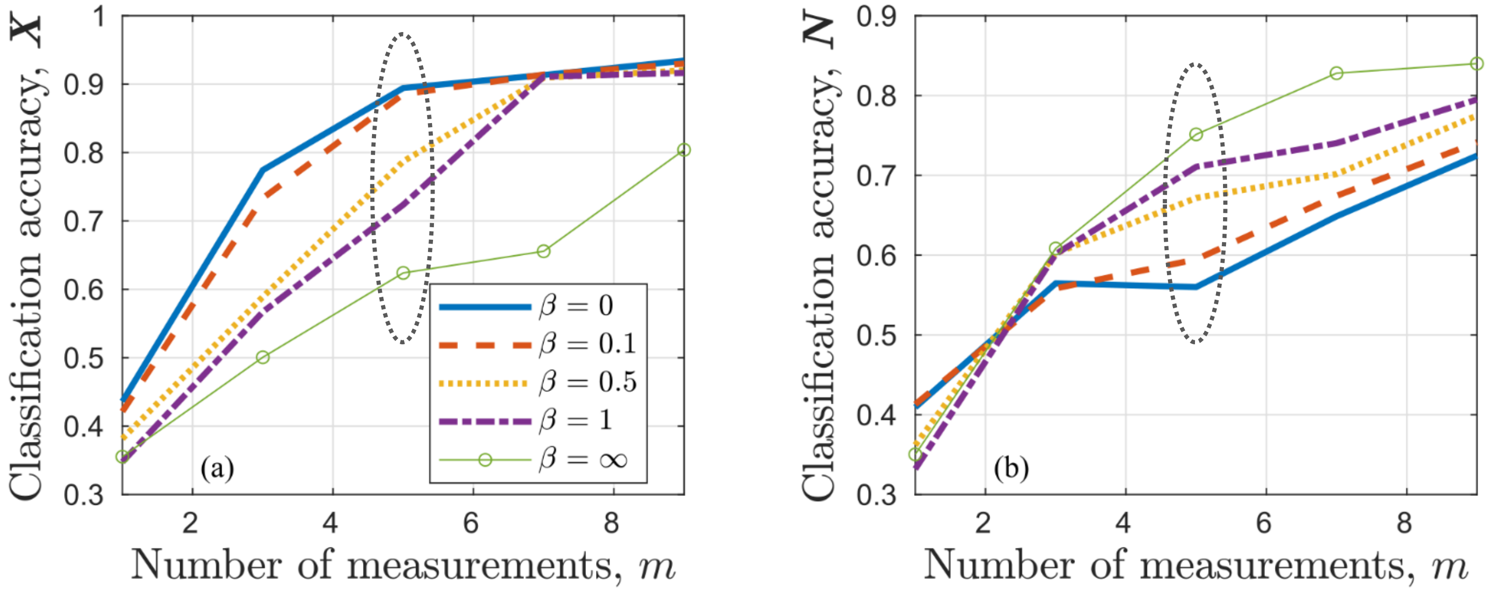

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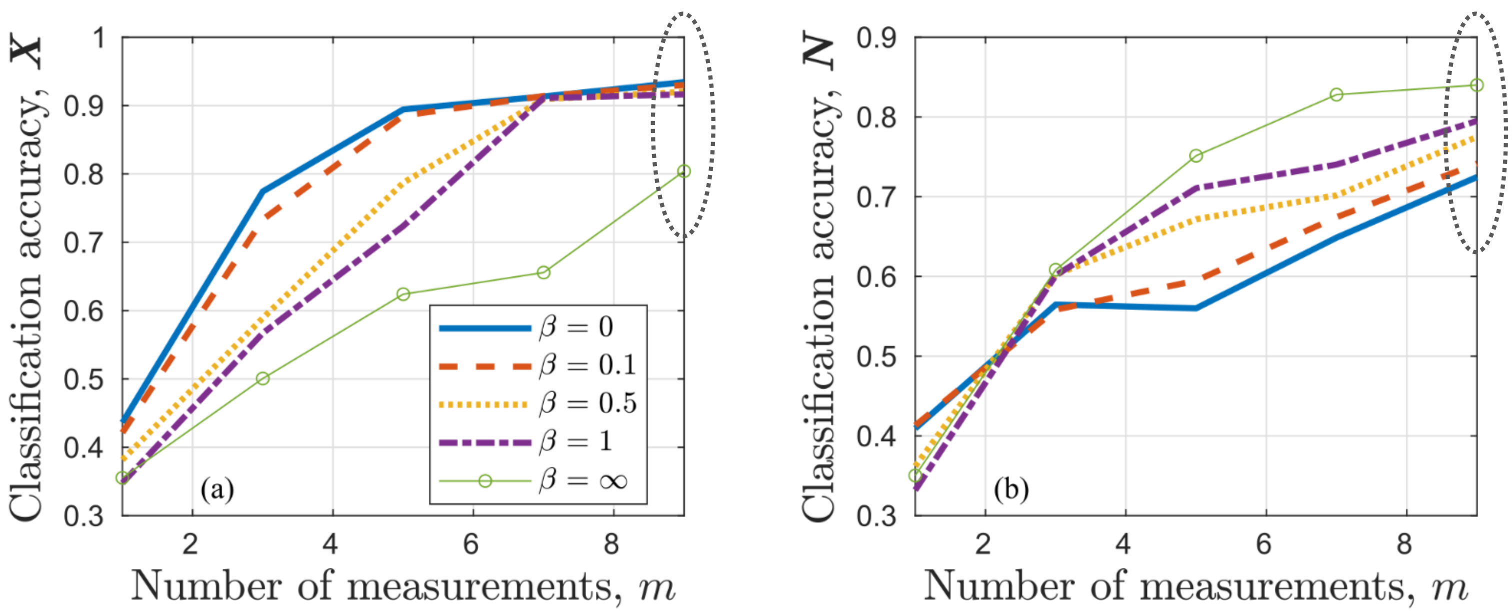

Conclusions and Future Work

- Sparse signal processing techniques find a wide variety of applications in electromagnetic signals and sensing
- We have described a novel approach to maximise energy efficiency for mm-wave communications systems using Dinkelbach method
- We have also shown how sparse sampling techniques can be designed to extract information about a signal of interest
- Desire to investigate theoretical limits to a wide range of problems with different availability of side information/prior knowledge
- PhD: “Data Driven Information Recovery in Sensor Systems”
  - **Kaiyu Zhang** investigating potential applications in communications and radar signal processing