A smart, yet cheap way to do spectrum sensing, using a priori knowledge

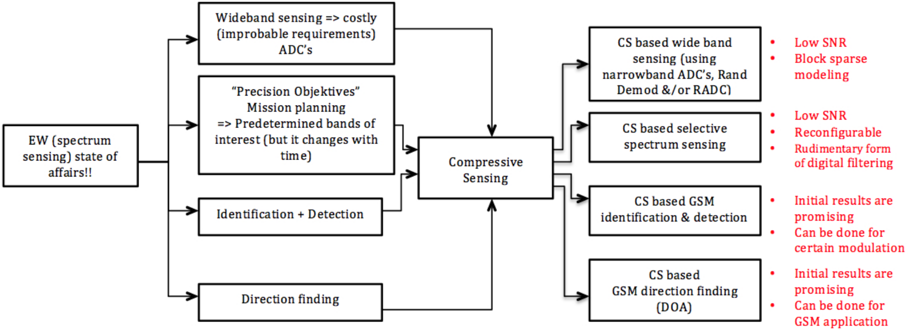
Ryno Verster
Supervisor: Dr. Amit Mishra
Co-supervisor: Prof Michael Inggs

University of Cape Town

September 5, 2013

Table of contents

Introduction



Overview

Purpose

- Provides a potential solution to manage data throughput
- Reduce bottlenecking – Acquisition
- Optimizing management of system resources
- Mine CS benefits for ES application and feasibility of implementation

Benefits

- Grow & maintain signal processing capabilities for Electronic Support systems.
- Reduce high throughput processing
- Allow for reconfigurability
- Enable signals and environments to be modelled sparsely

Current Work

Context

- Work presented today $\mapsto$ CS framework for spectrum sensing for use in ES
- Develop CS framework for GSM detection/identification
- Develop CS framework to determine the location of a specific GSM signal, via direction of arrival (DOA)
- Current research pursuits have been successful, in ALL domains.

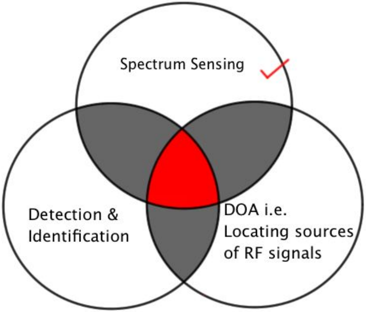


Figure – Illustration of the contextual domain of my work as it relates Electronic Warfare. Specifically dealing with GSM signals

CS: Main Concepts

Compressive Sensing

- Sub-Nyquist acquisition technique + Increase bit depth [1] [2]
- Uses randomization of input to reduce sample set
- Formalized through work done by Donoho & Candes [3]
- Uses algorithms to recover an estimate of the original signal

Steps Involved

1. Acquisition
2. Select Orthonormal Sparse Basis - Has to comply with R.I.P (i.e WHT, DFT, DCT, WDT, Modelled Transform)
3. Recovery via algorithms

Recovery Algorithms $\Rightarrow$ Iterative Methods (i.e. Linear programming, BP, Primal dual)
$\Rightarrow$ Greedy Algorithms (i.e. OMP, CoSaMP, MB-CoSaMP)

CS: Signal Model & Recovery

Model, Acquisition & Recovery

- **Signal Model**: The input signal is a time domain RF signal - sparse in the DFT basis

$$x(t) = \sum s_\omega e^{-2\pi i \omega t}$$

- **Acquisition**: Input signal is randomly sampled $y = \Phi x$
- **Recovery**: Estimate $\hat{s}$ from Y samples via l1 norm linear programming method. Solve for s!!

$$\hat{s} = \ argmin||v||_1 \ \text{ s.t } \ Y = Av$$

$$y = \begin{bmatrix} \ \Omega \ \end{bmatrix} \begin{bmatrix} X \end{bmatrix}$$

$$\Downarrow$$

$$y = \begin{bmatrix} \ \Omega \ \end{bmatrix} \begin{bmatrix} \ IDFT \ \end{bmatrix} \begin{bmatrix} s \end{bmatrix}$$

$$\Downarrow$$

$$y = \begin{bmatrix} \ A \ \end{bmatrix} \begin{bmatrix} s \end{bmatrix}$$

CS: Signal Model & Recovery

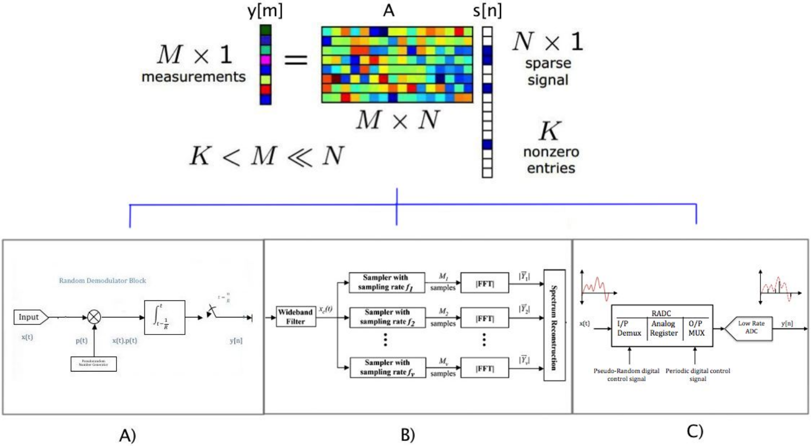


Figure – Illustration of CS signal model and. A - Random demodulator [4]. B - Parallel Prime Low sampler ADC [6]. C - Random ADC [5]

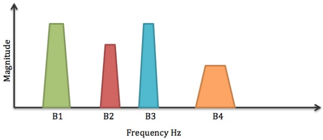
SImulation 1: Wideband Spectrum Recovery

Generated Signal Characteristics

$$x(t) = \sum_{n=1}^{M} \sqrt{E_n}.B_n.\text{sinc}(B_n(t-\Delta)) \times \cos(2\pi f_n(t-\Delta)) + w(t)$$ [a]

Description	Quantities	Symbols
No. of Signals	9	M
Bandwidths	0-50 MHz	B_n
Time delays	0 - 20 μ s	Δ
Sampling Time	2	T_s
Energy of Signals	1-7dB	$\sqrt{E_n}$
Noise (AWGN)	0-20dB	$w(t)$

[a] Signal generation simulation closely follows that of [6]



SImulation 1: Wideband Spectrum Recovery

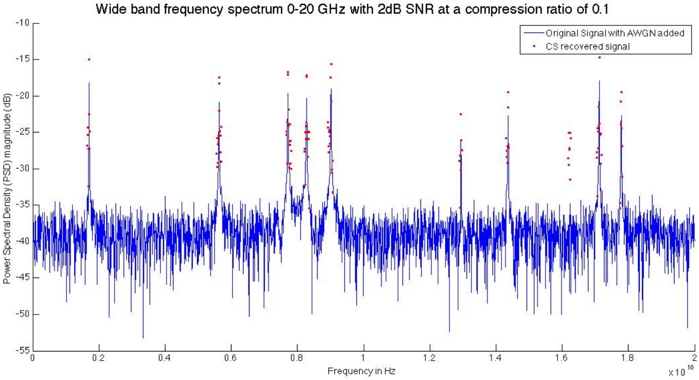


Figure – showing the power spectral density (PSD) of the recovered CS signal of against the same signal as before but showing the added noise power

Simulation 1: cont'd

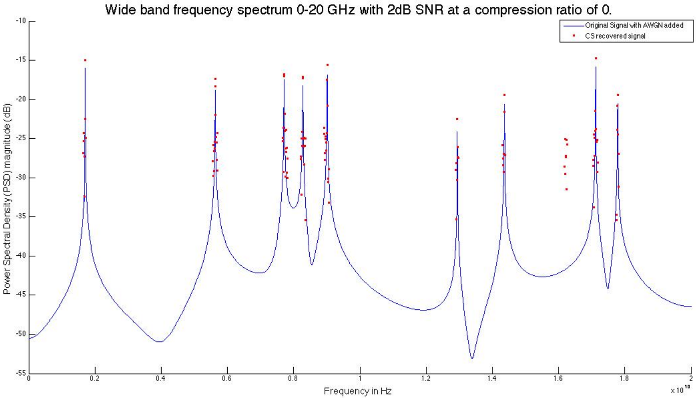


Figure – showing the power spectral density (PSD) of the recovered CS signal against the same signal as before but showing no noise power added

Simulation 1: cont'd

Recovery Error of Estimates for Different Recovery Algorithms

Table: *Showing the nMSE for different CS recovery algorithms varying the compression ratio's for spectral estimation of the wide band input signal*

	Compression Ratio (M/N)		
Algorithm	**0.5**	**0.2**	**0.1**
BP	0.0980	0.4195	0.4425
OMP	0.0949	0.1045	0.253
CoSaMP	0.0960	0.1186	0.251
MB-CoSaMP	0.0204	0.0458	0.0891

Simulation 2: Selective Spectrum Sensing

Input Signal

Same wide band signal, with an added GSM 900 uplink band that is at a carrier frequency of 898.5 MHz with a bandwidth of 25 MHz

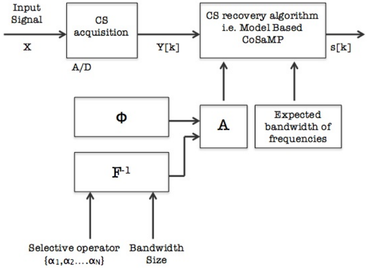


Figure – Illustrating the system block diagram of how selective spectrum sensing is implemented. The quantized signal $y[k]$ sampled by compressive means is recovered via a biased matrix, depicted by A. which has a final output spectrum estimate $s[k]$. The recovery algorithm needs both the A and the expected bandwidth of The inverse Fourier matrix F^{-1} is biased by the input parameters α which take on either a high value or low value, similar to a binary process. This combined with the bandwidth of interest as an input allows the construction of the biased Fourier matrix.

Simulation 2: Signal Model and Setup cont'd

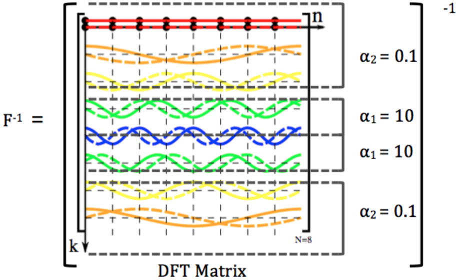


Figure – Illustration of the operation of selective spectrum sensing which generates the inverse Fourier matrix. The coefficients α_1 and α_2 merely show the bands that are biased by a generic value, namely 0.1 and 10. This allows for selectively biasing certain bands in the DFT matrix. Diagram modified by author from [7]

Simulation 2: nMSE – High SNR

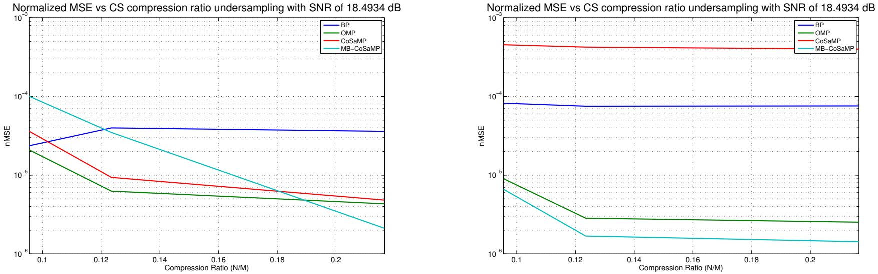


Figure – showing the normalized mean squared error (nMSE) for sampling compression ratio less than 0.2 of the selected GSM spectrum within a high SNR environment, i.e. 18 dB. Left - Normal recovery. Right - Selective Recovery

Simulation 2: nMSE – Medium SNR

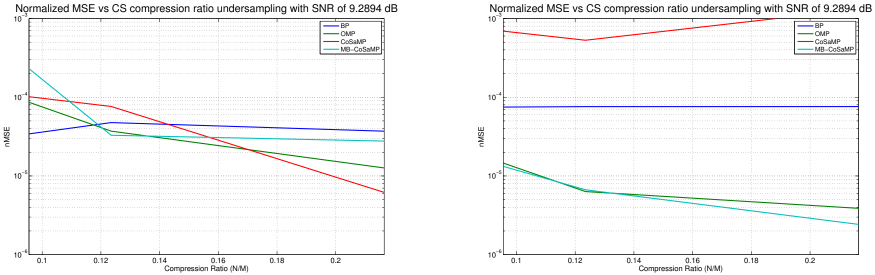
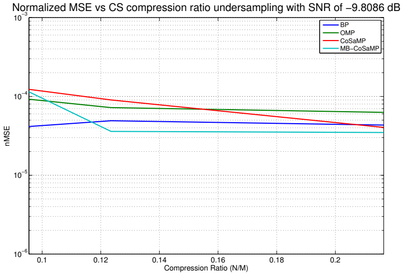


Figure – showing the normalized mean squared error (nMSE) for sampling compression ratio less than 0.2 of the selected GSM spectrum within a medium SNR environment, i.e. 9 dB. Left - Normal recovery. Right - Selective Recovery

Simulation 2: nMSE – Low SNR



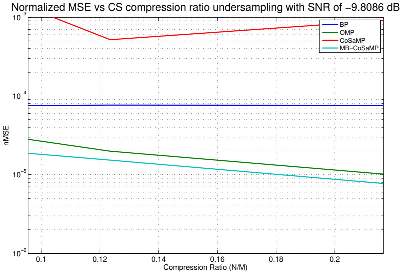


Figure – showing the normalized mean squared error (nMSE) for sampling compression ratio less than 0.2 of the selected GSM spectrum within a low SNR environment, i.e. -9 dB. Left - Normal recovery. Right - Selective Recovery

Simulation 2: Computational Time

Figure – showing the computational time for all four CS recovery signals using normal recovery, subject to different compression ratios in a high, medium and low SNR environment

	Compression Ratio (M/N)								
Algorithm	**0.07**	**0.1**	**0.2**	**0.07**	**0.1**	**0.2**	**0.07**	**0.1**	**0.2**
XP	0.7105	0.8613	1.8833	0.3492	0.8654	1.8534	1.6342	0.8621	1.6342
OMP	0.0702	0.1101	0.2110	0.0593	0.1049	0.1911	0.0757	0.0986	0.1784
CoSaMP	0.3429	0.4970	0.8870	0.3072	0.4797	0.8982	0.3852	0.5057	0.8588
MB-CoSaMP	0.06825	0.1925	0.2473	0.20148	0.21706	0.0981	0.05418	0.2265	0.2325
	SNR: 18dB			SNR: 9dB			SNR : -9dB		

Figure –showing the computational time for all four CS recovery signals using selective spectrum sensing recovery, subject to different compression ratios in a high, medium, low SNR environment

	Compression Ratio (M/N)								
Algorithm	**0.07**	**0.1**	**0.2**	**0.07**	**0.1**	**0.2**	**0.07**	**0.1**	**0.2**
XP	0.6934	0.8629	1.9873	0.6434	0.7911	1.8444	0.6837	0.8306	1.7202
OMP	0.0721	0.0980	0.2201	0.0651	0.0978	0.1910	0.07617	0.0906	0.1784
CoSaMP	0.3245	0.4479	0.7492	0.3094	0.4777	0.7253	0.7016	0.4554	0.3826
MB-CoSaMP	0.041	0.1356	0.3385	0.0733	0.1652	0.2806	0.11516	0.1545	0.2945
	SNR: 18dB			SNR: 9dB			SNR : -9dB		

Application & Use

- The idea of selective spectrum sensing has the capability of being reconfigurable from an SDR perspective and application
- Used for exclusive use in GSM bands
- More accurately estimate and detect specific operating bands used by a user within GSM
- Applied in the correct way, possible bit depth could also be achieved (i.e. HackRF and other SDR platforms with low bit depth)

Disclaimer

- As a sub-nyquist technique – Compressive Sensing is not the answer to all signal processing problems. However, if modelled in an intelligent way it can result phenomenal results
- Research initiative still needed in the field of Compressive Sensing for better performance

Conclusions

- Wide band spectrum sensing using CS –> Realizable with newer algorithms i.e. MB-CoSaMP recovery algorithm
- Selectively spectrum sensing works and improves spectral error recovery in severe signal to noise ratio (SNR) conditions
- This can only be achieved based on the a priori knowledge of the spectrum, which in most scenarios for EW systems are available.

Future Work

- Do selective spectrum sensing on real GSM data
- Improve estimation of specific GSM signals within the uplink and downlink bands
- Detection / Identification of GSM signals using CS
- Direction of Arrival DOA (i.e. Locating signals of Interest) Specifically for GSM signals using CS means

Comments / Questions

Thank You

ARMSCOR

CSIR
our future through science

References

[1] L. Jacques, J. N. Laska, P. T. Boufounos, and R. G. Baraniuk, "Robust 1-bit compressive sensing via binary stable embeddings of sparse vectors," 2011.

[2] Y. Plan and R. Vershynin, "One-bit compressed sensing by linear programming," *Communications on Pure and Applied Mathematics*, 2013.

[3] D. L. Donoho, "Compressed sensing," *Information Theory, IEEE Transactions on*, vol. 52, no. 4, pp. 1289–1306, 2006.

[4] J. A. Tropp, J. N. Laska, M. F. Duarte, J. K. Romberg, and R. G. Baraniuk, "Beyond nyquist: Efficient sampling of sparse bandlimited signals," *Information Theory, IEEE Transactions on*, vol. 56, no. 1, pp. 520–544, 2010.

[5] J. Laska, S. Kirolos, Y. Massoud, R. Baraniuk, A. Gilbert, M. Iwen, and M. Strauss, "Random sampling for analog-to-information conversion of wideband signals," in *Design, Applications, Integration and Software, 2006 IEEE Dallas/CAS Workshop on*. IEEE, 2006, pp. 119–122.

[6] H. Sun, W. Chiu, J. Jiang, A. Nallanathan, and H. Poor, "Wideband spectrum sensing with sub-nyquist sampling in cognitive radios," 2012.

[7] Fourierop rows only. [Online]. Available: http://upload.wikimedia.org