A SPECTRUM SENSOR FOR CUBESAT RADIOS

In The Proceedings of The
3rd BIANNUAL IEEE COGNITIVE COMMUNICATIONS FOR AEROSPACE APPLICATIONS WORKSHOP
JUNE 21-22, 2021

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ABSTRACT

Cube satellite (CubeSat) launches have increased exponentially over the last 20 years. This class of miniature spacecraft is well-suited for a set of nonconventional satellite architectures collectively known as formation flying. With the exponential pace of launches expected to continue, the prospect of spectrum management for these complex formations arises. In previous work, investigators focus on terrestrial applications of spectrum sensing, which have the luxury to utilize hardware with high size, weight, and power (SWaP) resources. *In this work, we develop and test a spectrum sensor for CubeSat radio applications.*

Given that CubeSat radios are inherently designed for low SWaP, they cannot implement the computationally expensive spectral correlation analyzer (SCA) algorithms for signal detection. To that end, our investigation focuses on the application of the SCA to square-root-raised-cosine (SRRC) pulse-shaped quadrature amplitude modulation (QAM) waveforms using a field-programmable gate array (FPGA). This model requires no prior knowledge of the radio-frequency (RF) channel. We show that this model can consistently and accurately detect the symbol rate and center frequencies of waveforms located in a spectrum.

Index Terms—cubesat, spectrum sensing, spectral correlation analyzer, fpga

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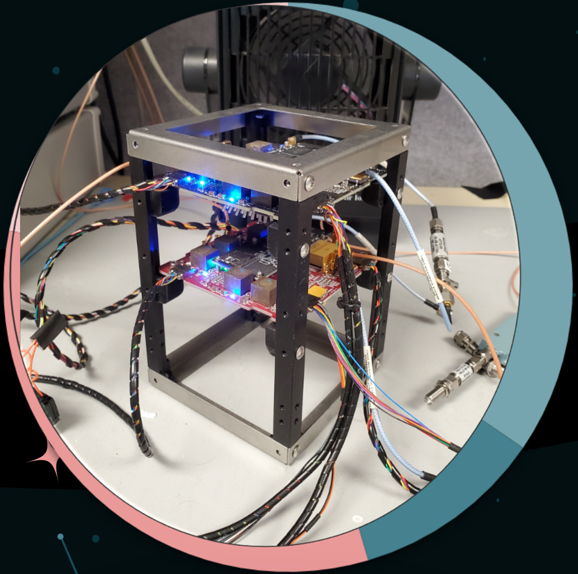
1.

INTRODUCTION

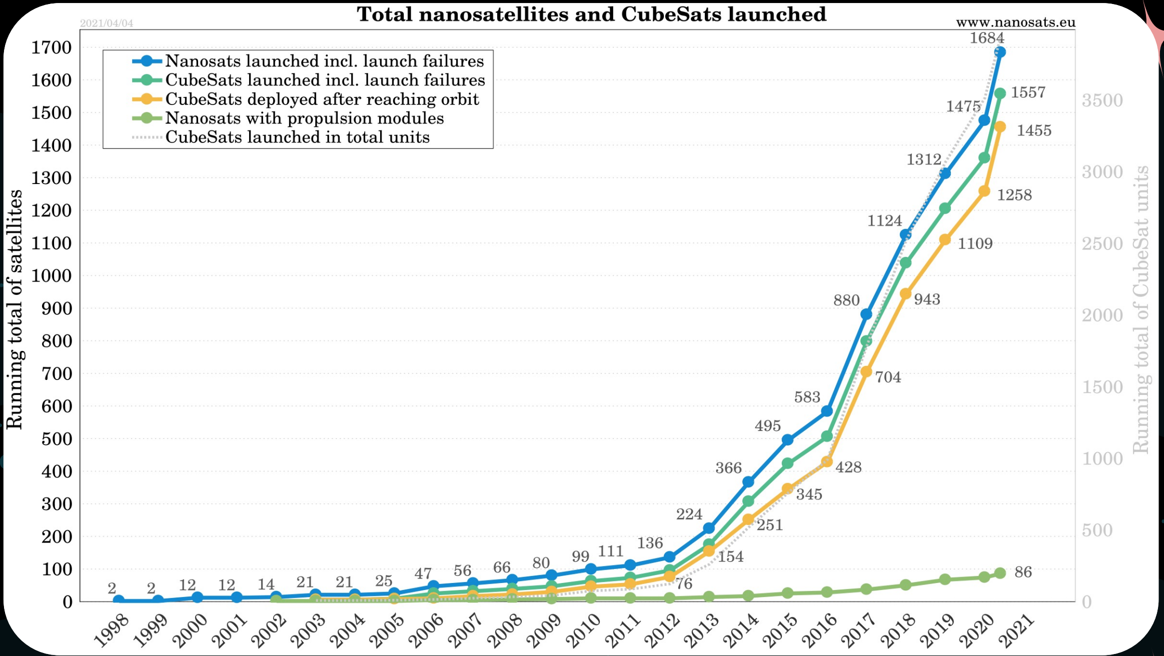
‘Where shall I begin, please your Majesty?’ he asked. ‘Begin at the beginning,’ the King said, gravely, ‘and go on till you come to the end: then stop.’

–Lewis Carroll

CubeSats

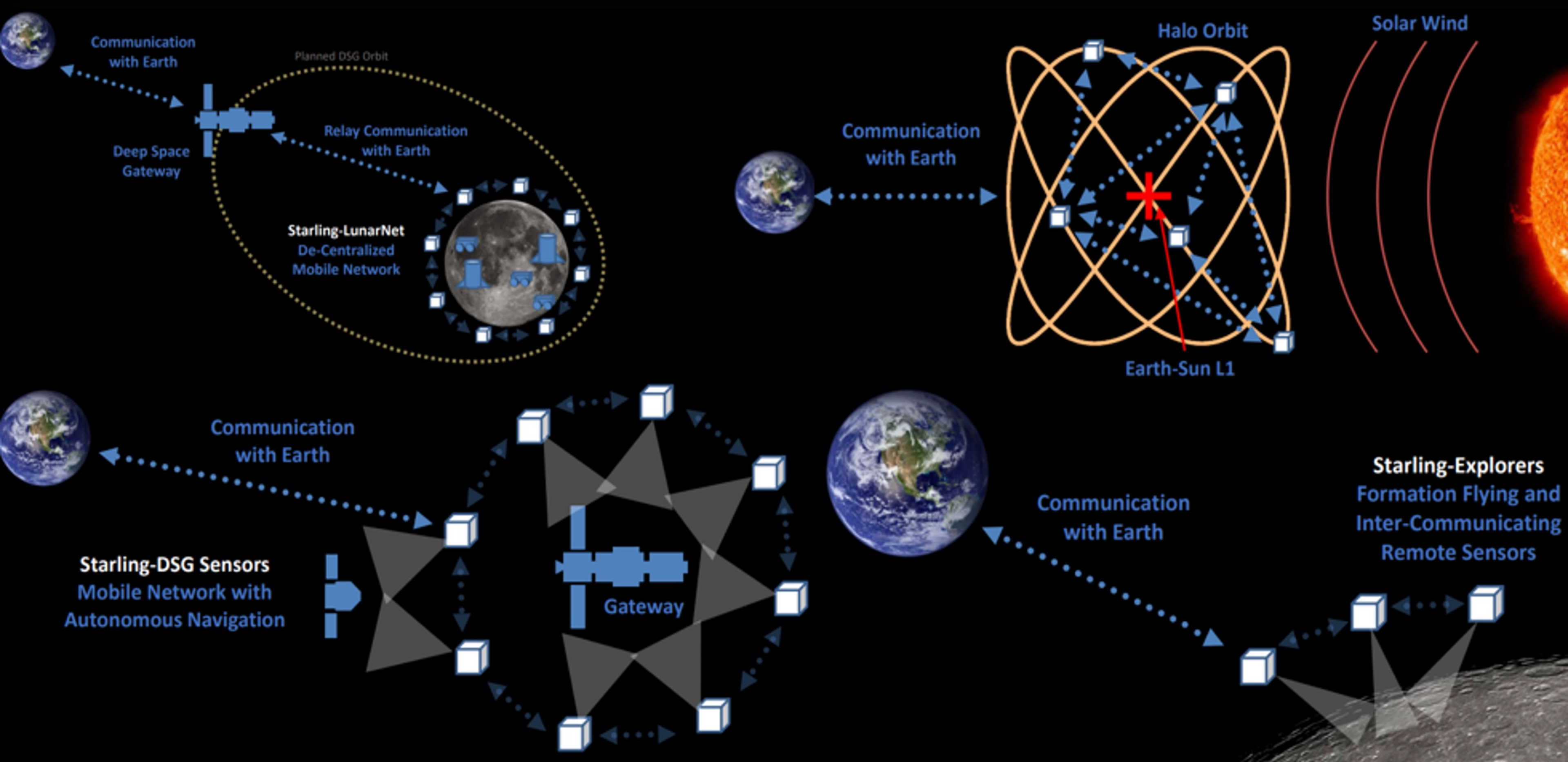


NASA GRC AstroSDR
CubeSat Radio

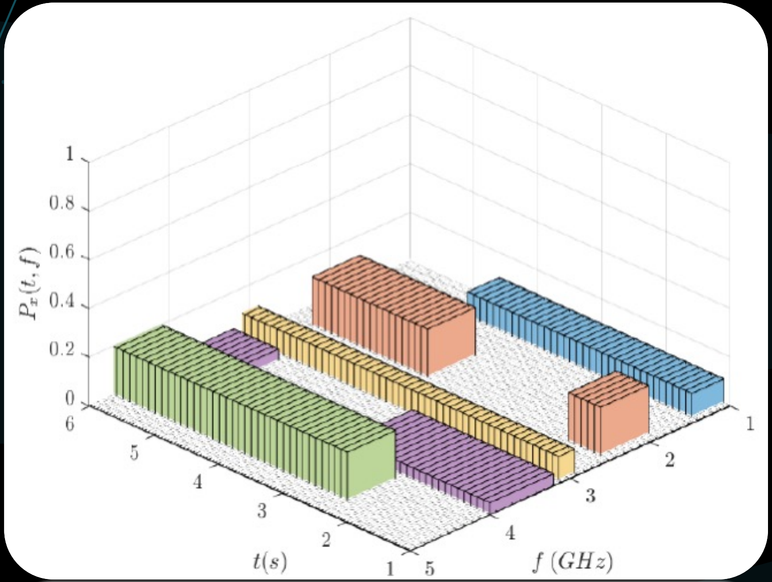


Running total of CubeSat launches over the last two decades

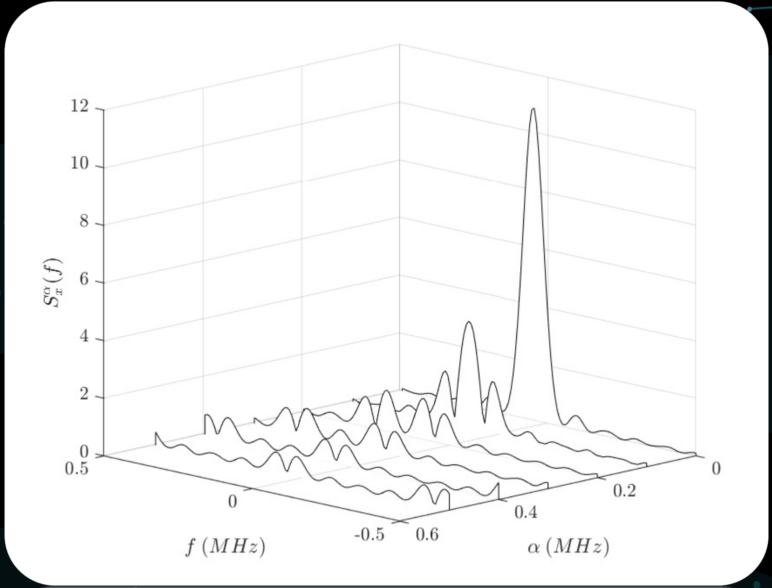
CubeSat Swarms: *NASA AMES Starling 1 Missions*



Spectral Sensing



Example of spectral use over time. Using spectrum sensing we can maintain awareness of where and when licensed users or interferers are active.



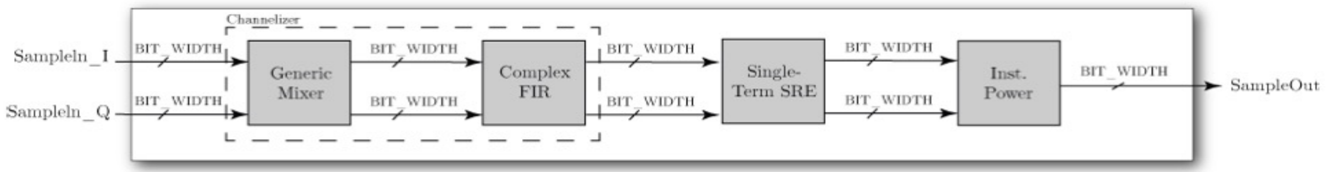
Example of estimation results produced by a spectral correlation analyzer (SCA). The peaks correspond to various waveform features.

The Streaming Spectral Correlation Analyzer (Streaming-SCA):

Blind Symbol Rate-Center Frequency *Estimation*

$$S_X^{v}[k] = \frac{1}{N}\sum_{n=0}^{N-1} \left|(X[n]e^{-j2\pi kn}) * h[n]\right|^2 e^{-j2\pi vn}$$

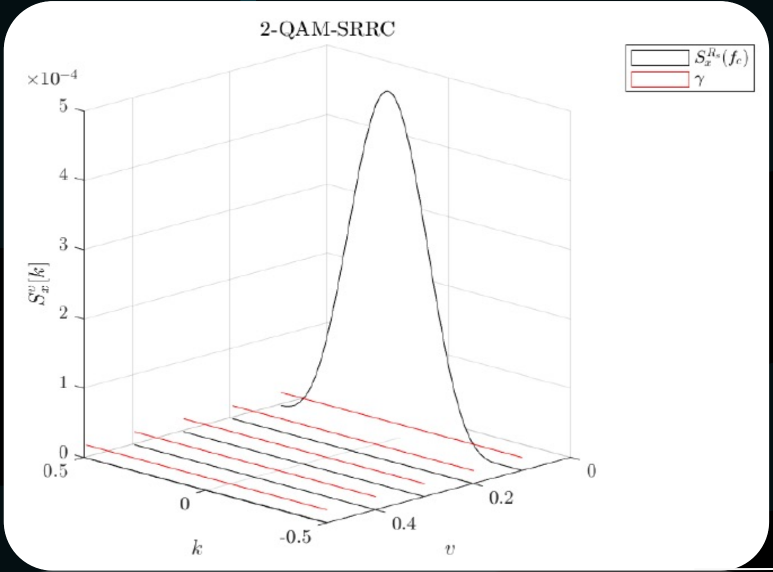
Equation of the streaming-SCA.



Digital logic block diagram of the streaming-SCA.

The Streaming Spectral Correlation Analyzer (Streaming-SCA):

Blind Symbol Rate-Center Frequency *Detection*



$$|S_X^v[k]|^2 \underset{H_0}{\overset{H_1}{\gtrless}} \beta \left(\frac{1}{N} \sum_{n=0}^{N-1} |X[n]|^2 \right)^2$$

Detection is performed by comparing the test statistic of the estimate (lhs) with a threshold (rhs).

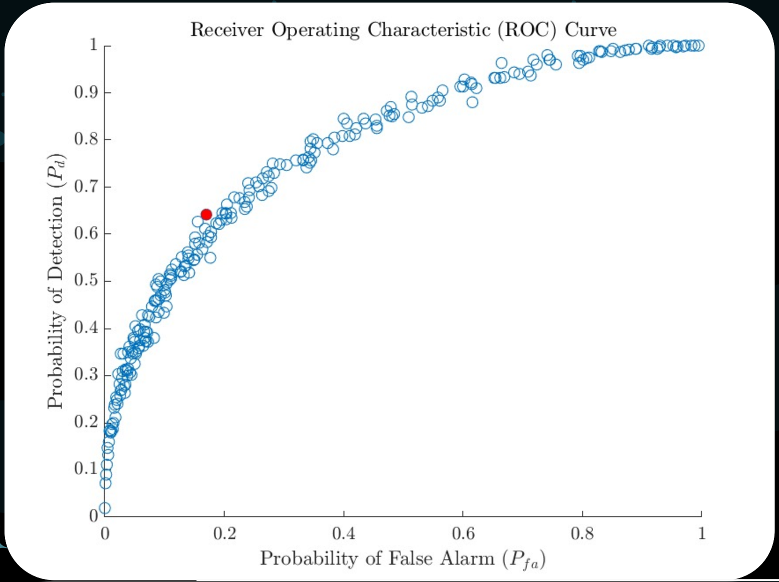
Using our binary hypothesis test, we can differentiate between false alarms and true detections. The red threshold is proportional to beta. The peak of each detected streaming-SCA instance corresponds exactly to the true symbol rate and center frequency of the received waveform.

The Optimal Threshold

TABLE I
CO-CHANNEL INTERFERENCE USED FOR THE GENERATION OF AN ROC CURVE

#	N	F_s	R_s	f_c	M	r	E_b/N_0
0	2^{12}	$1.0MHz$	$0.1MBd$	$0.1MHz$	32	0.2	$3.0dB$
1	2^{12}	$1.0MHz$	$0.2MBd$	$0.2MHz$	32	0.2	$3.0dB$

Noisy, interfering signals used to generate ROC curve.



$$J = \frac{\sum P_d}{\sum P_d + \sum (1 - P_{fa})} + \frac{(\sum 1 - P_d)}{(\sum 1 - P_d) + \sum P_{fa}} - 1$$

Youden's J Statistic determines the optimal threshold of our test signal, which in turn is used to find the optimal beta of our detector.

Ability of our detector to properly classify signals as its threshold is varied.

II.

IMPLEMENTATION

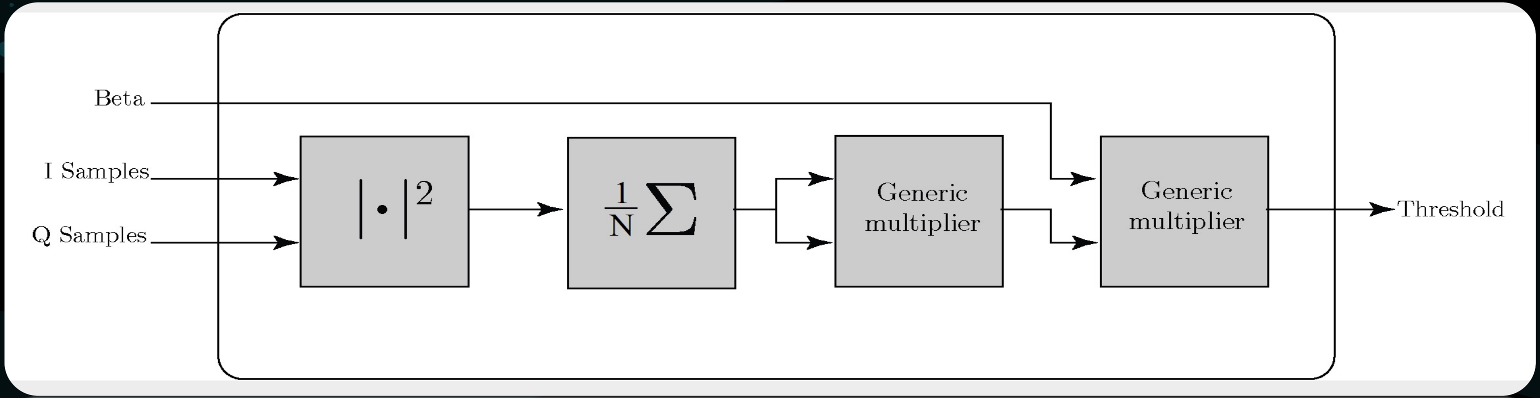
If you don't know where you're going any road can take you there.

–Lewis Carroll

Threshold

$$\beta\left(\frac{1}{N}\sum_{n=0}^{N-1}|X[n]|^2\right)^2$$

The optimal threshold as determined by our ROC.



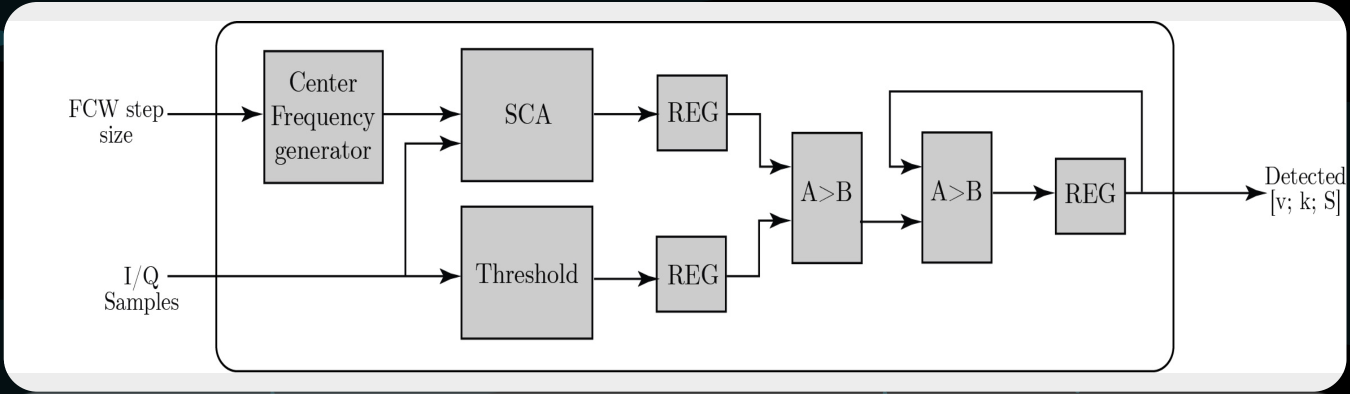
Digital Logic block diagram of the optimal threshold.

Blind Symbol Rate-Center Frequency Detector

$$|S_X^v[k]|^2 \underset{H_0}{\overset{H_1}{\gtrless}} \beta \left(\frac{1}{N}\sum_{n=0}^{N-1}|X[n]|^2\right)^2$$

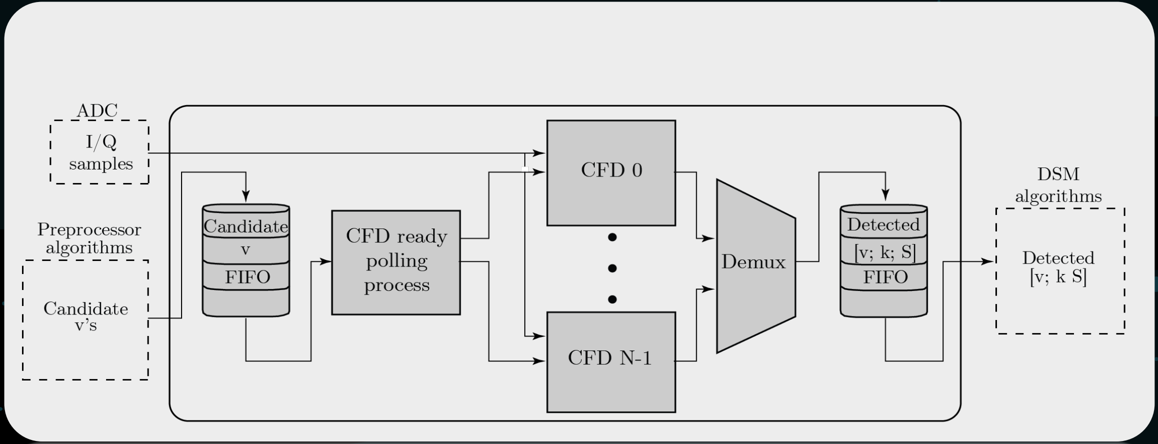
lhs: *Estimate of the correlation between a center frequency, a symbol rate, and the incoming samples.*

rhs: *Its optimal threshold.*



Digital logic block diagram of the detector.

Spectrum Sensor



Block diagram of the spectrum sensor.

Flexible to accommodate resources available on CubeSat.

Can blindly sense entire spectrum, or if a preprocessing algorithm is used, can function as a faster semi-blind spectrum sensor.

Results are stored in a data structure to be used to make ***intelligent decisions of when to transmit, where to transmit, and at what rate!***

III.

Results

"It would be so nice if something made sense for a change."

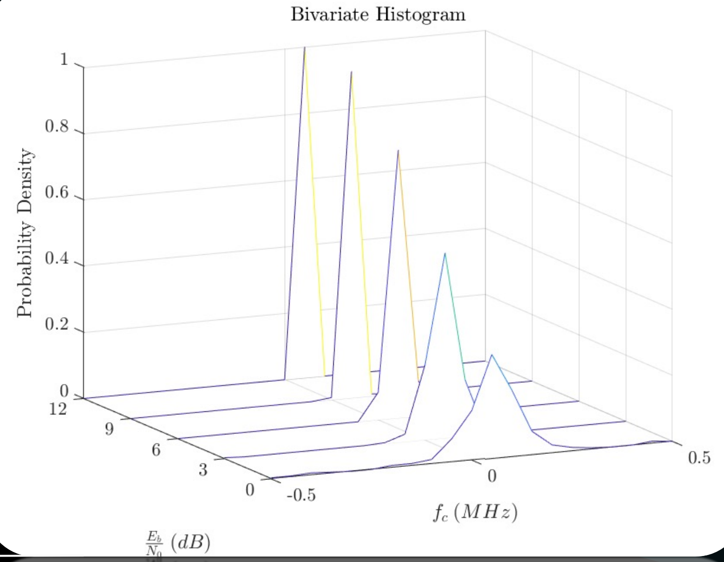
–Lewis Carroll

Characterization

TABLE II
SPECTRUM SENSOR PERFORMANCE

Experiment #	E_b/N_0 (dB)	r	P_d	P_{fa}
baseline	15.0	0.35	1.0	0.0013
1	12.0	0.35	1.0	0.0284
2	9.0	0.35	1.0	0.0584
3	6.0	0.35	1.0	0.0854
4	3.0	0.35	0.9967	0.1146
5	0.0	0.35	0.89	0.1213
6	15.0	0.30	1.0	0.0108
7	15.0	0.25	1.0	0.0108
8	15.0	0.20	1.0	0.0150

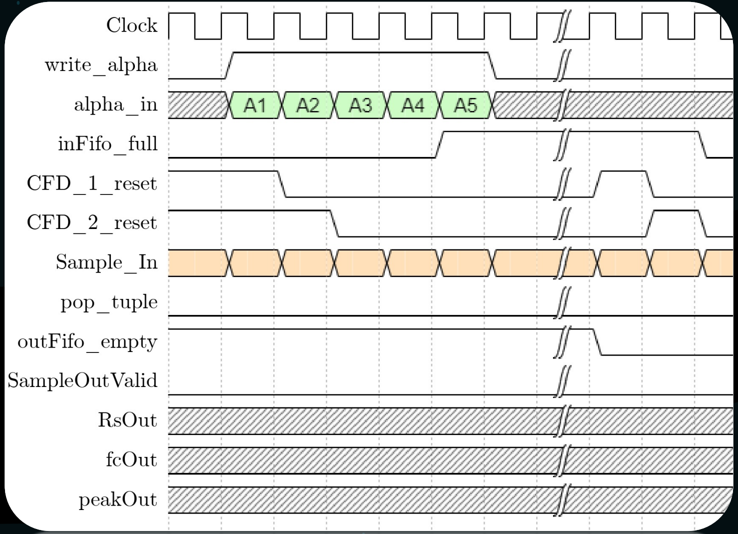
Even for an E_b/N_0 of 0, the probability of detection is nearly perfect! This is shown with a high detection resolution, however.



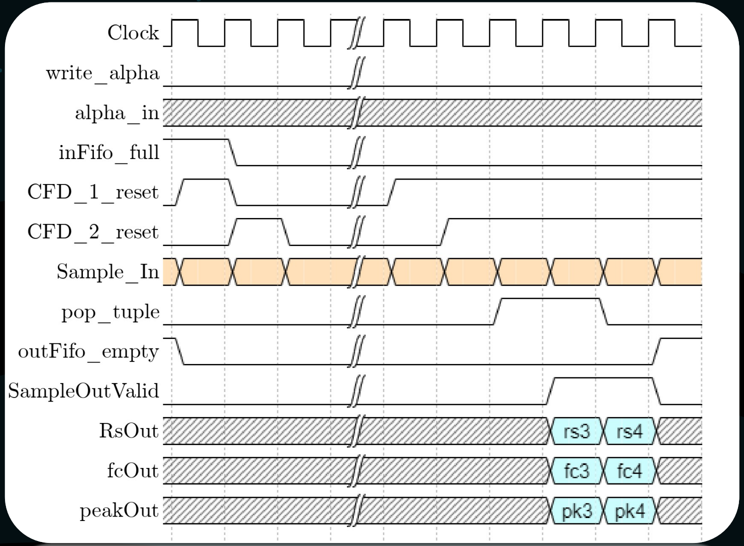
The tradeoff is performance speed vs resolution. We can intelligently determine an appropriate resolution by characterizing the frequency offset tolerance.

Timing

Input – Candidate symbol rates to be searched.



Output – Detected waveforms values.



IV.

CONCLUSION

“One of the hardest things in the world is to convey a meaning accurately from one mind to another.”

–Lewis Carroll

Summary

CubeSat Swarms

Streaming-SCA

Spectrum Sensing

Future Work

- Characterization of waveforms outside of M-QAM-SRRC.
- Development of symbol rate pre-processor.
- Increased performance when ADC is faster than FPGA via decimation.
- Resource reduction of streaming-SCA with Goertzel filter.

Acknowledgements

- NASA's Cognitive Communications Project supported this work.
- Erica K. Henrichsen provided graphic design support.

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