

THE VALUE OF PERFORMANCE.

## Survey of Machine Learning Methods for Wideband Space Cognitive Antenna

IEEE Cognitive Communications for Aerospace Applications Conference

June 25-26, 2019

Samuel Vineyard

Systems Engineer

Co-authors

Suzanna LaMar & Todd Gillette

DISTRIBUTION STATEMENT. Approved For Public Release #19-1146; Unlimited Distribution.

## Topics

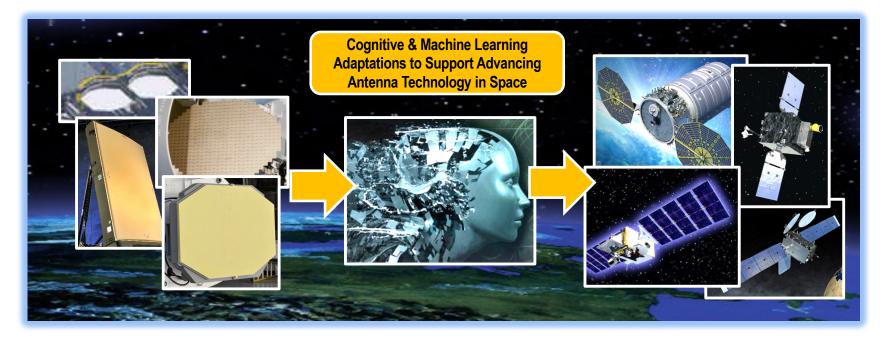


- Introduction
- Machine Learning Pedigree & Examples
- Cognitive Antenna Motivation
- Cognitive Mission Workflow
- Example Interference Mitigation Scenario
- Dynamic Spectrum Access (DSA) Capability
- State-of-the-Art Survey
- Trade Space Evaluation Process
- Vision for the Future Next Generation SCaN Architecture
- Summary

#### Introduction

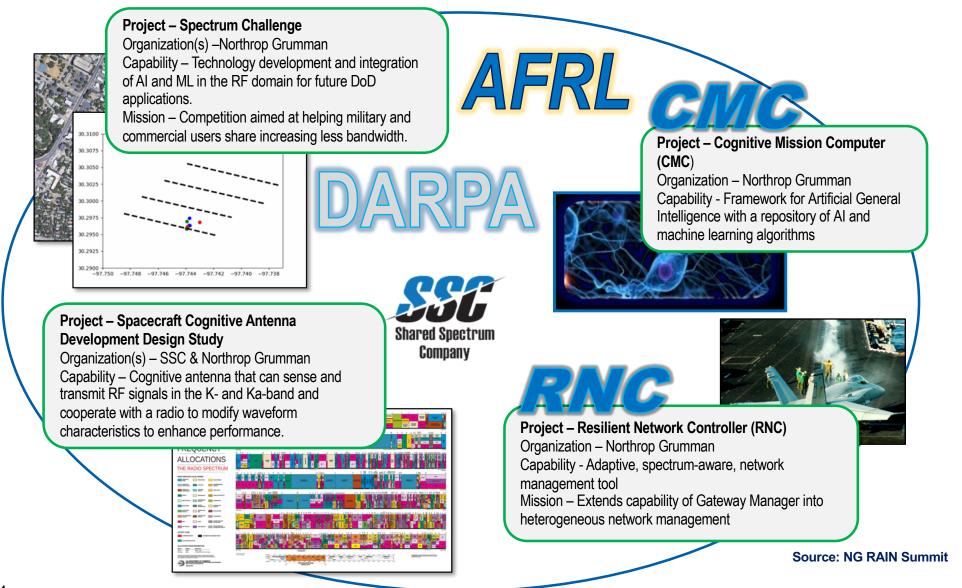


- Cognitive Radios built on software defined radio (SDR) platforms are being developed and matured to address the problem of spectrum underutilization.
- Commercial technology investments are pushing the limits of reconfigurability, processing, and networking within the space communications architecture.
- As the development evolves to increasingly wideband capability, it is important to complement it with **advanced ultra-wideband antenna technology** for the future (e.g. support spectrum services for both commercial and defense frequency bands).
- The advent of **machine learning and cognition** provides an opportunity for this antenna of the future to not only react to adverse conditions, but learn to optimize its configuration for future scenarios within the complex, dynamic spacecraft environment i.e. become a **cognitive antenna**.



## Machine Learning Pedigree and Examples





## **Cognitive Antenna Motivation**

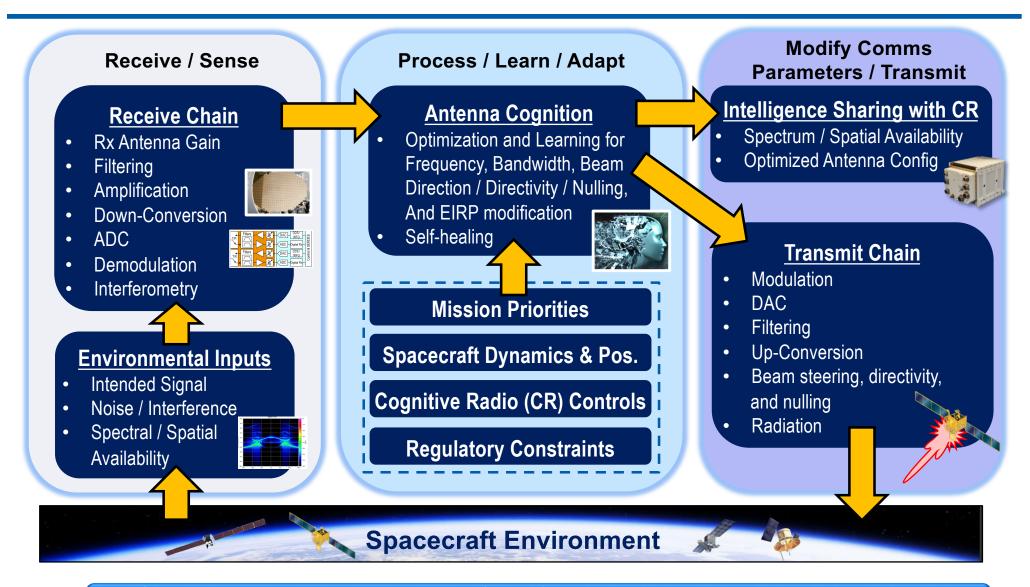


- Cognitive Radio (CR): Defined as a radio with the ability to change its transmitter parameters based on interaction with the environment in which it operates, Source: Federal Communications Commission (FCC).
- **Cognitive Antenna (CA):** Defined as an environmentally perceptive antenna that can dynamically allocate bandwidth and / or adjust beam direction and directivity (beamwidth), EIRP, provide beam nulling, etc. to optimize spectral, spatial and temporal resources to complement cognitive radio technology, Source: National Aeronautics and Space Administration (NASA).

No.	Category	System Goals
1	Frequency	The Cognitive Antenna shall operate anywhere from 18 GHz to 33 GHz.
2	Bandwidth	The Cognitive Antenna shall have an adjustable bandwidth from 10 MHz to 200 MHz.
3	Beamwidth	The Cognitive Antenna shall support an arbitrary beamwidth for variable data rates.
4	Coverage	The Cognitive Antenna shall provide Hemispherical coverage.
5	Beams	The Cognitive Antenna shall support at least four (4) independent beams.
6	EIRP	The Cognitive Antenna shall support variable EIRP dependent on use case applications.
7	Nulling	The Cognitive Antenna shall provide directional nulling to minimize interference.
8	Power	The Cognitive Antenna shall support low power per channel, e.g. <500 mW where feasible.
9	Interoperability	The Cognitive Antenna shall be interactive with a Cognitive Radio.
5		

## **Cognitive Mission Workflow**

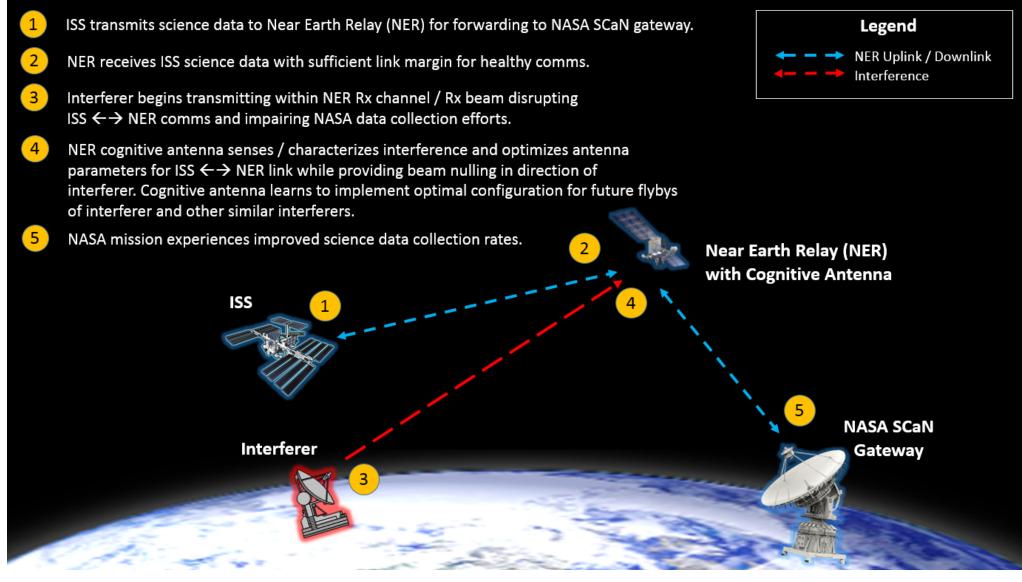




Cognitive Antenna mission is to adapt to / learn from the environment and dynamically adjust its parameters to improve end-to-end communications performance.

# Example Interference Mitigation Scenario with Cognitive Antenna

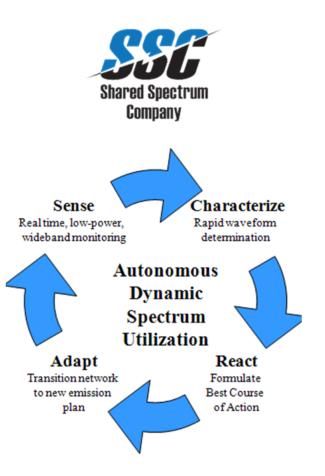




## Advanced Autonomous Dynamic Spectrum Access (DSA)



- DSA: A spectrum sharing approach that provides real-time conditional access to spectrum that would otherwise be unavailable
- Conditional access is based on spectrum policy constraints and local spectrum utilization to minimize cross-system interference
- DSA technology enables radios to share multiple frequency bands without interfering with legacy and otherwise protected systems
- Frequency adaptation maintains and restores network topology in dynamic spectrum conditions
- Decentralized, autonomous, follows commander's intent and spectrum manager's policy



SSC's DSA provides autonomous decentralized operations for greatly increased network survivability.

## State-of-the-Art Survey – Exploring Potential Algorithm Implementations for the Cognitive Antenna



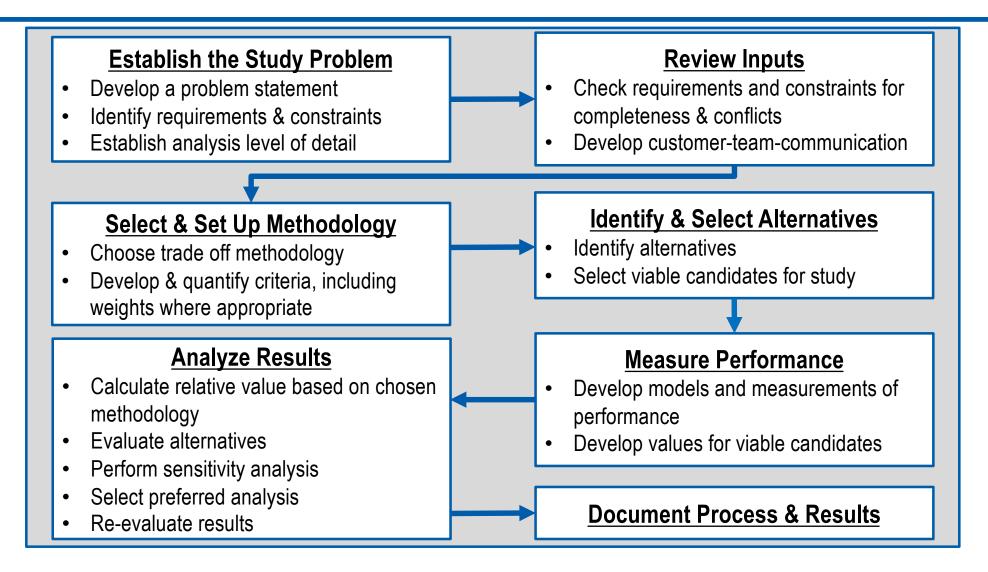
Algorithm	Description	Applicability to Cognitive Antenna
Bayesian Learning	Updates beliefs about elements in the system based on observations	Estimation of other secondary user activity in a repeated auction for spectrum access <sup>1</sup>
Hidden Markov Model (HMM)	A process of deriving a model of states, observations probabilities, and state transitions	Prediction in spectrum sensing, decision, sharing, and mobility <sup>2</sup>
Support Vector Machines (SVM)	A classifier that learns given a function (separation shape) or kernel enabling classification of complicated data spaces	Signal identification <sup>3</sup> , protocol identification <sup>4</sup>
Multilayer Perceptron Neural Network	Learns non-linear transformation of inputs to produce outputs with real values, classifications, or action selections	Beamforming capability driven by neural network elements <sup>5</sup> ;
Convolutional Neural Network	Neural network performing the same set of operations (e.g. filters) over all elements in an array	Indoor localization <sup>6</sup> ; direction of arrival estimation <sup>7</sup> ; proposed: receive processing for an AESA where local signal deviation and dynamics may indicate informative environmental effects
Recurrent Neural Network e.g. Long Short Term Memory (LSTM)	Prior states enable learning and processing of temporal patterns	Proposed: Training neural network receive beamformer / nulling parameter selection given prior spatial-temporal signal and using SINR for reinforcement
Reinforcement Learning (Q- Learning)	Estimate system state and policy for parameter / action selection given the estimated state; learn using positive and negative reinforcement	

State-of-the-art cognitive communications algorithms provide a vast trade space for Cognitive Antenna

## Trade Space Evaluation Process

10

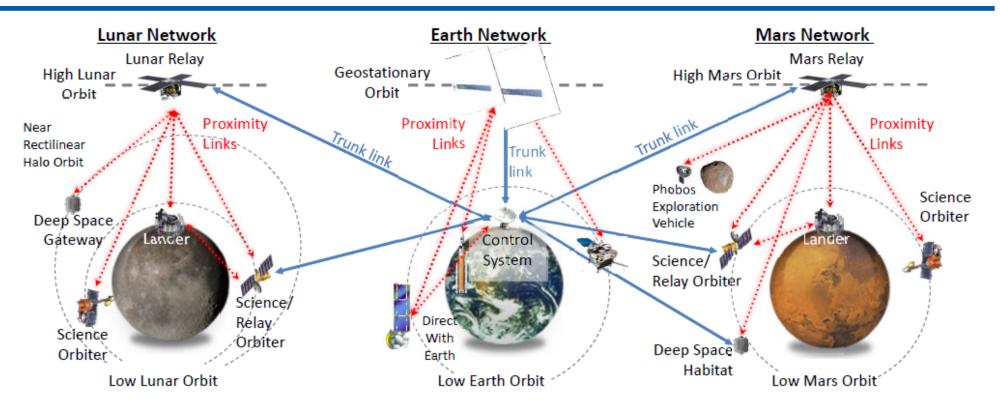




Through an agile, proven-trade evaluation process and utilization of internal engineering expertise, we will determine the feasibility of a Cognitive Antenna that meets / exceeds NASA's goals. Use or disclosure of data contained on this page is subject to the restrictions on the title page of this document.

## Vision for the Future - Next Generation SCaN Architecture





- While the Near Earth Network (NEN) is the primary focus of this feasibility study, Lunar and Mars architectures are also of high interest for a cognitive antenna application and will be explored.
- The benefits of autonomous communications optimization and learning extends beyond our planet and has the potential to greatly enhance mission resilience and overall performance.



- As cognitive radio technology becomes more prominent in the space • communications domain, it is imperative that a complementary **ultra-wideband** cognitive antenna is developed.
- Northrop Grumman and Shared Spectrum Company are developing the • hardware and cognitive architecture of a K / Ka-band cognitive antenna to ascertain its feasibility within the next-gen NASA SCaN architecture.
- The conclusions of this study will determine whether there is an opportunity to develop and implement a cognitive antenna technology demonstrator.





- 1. Repeated Auctions with Bayesian Nonparametric Learning for Spectrum Access in Cognitive Radio Networks. 2011. https://ieeexplore.ieee.org/abstract/document/5692900
- 2. Spectrum prediction in cognitive radio networks. 2013. https://ieeexplore.ieee.org/abstract/document/6507399
- 3. Signal Classification Based on Spectral Correlation Analysis and SVM in Cognitive Radio. 2008. https://ieeexplore.ieee.org/abstract/document/4482799
- 4. MAC protocol identification using support vector machines for cognitive radio networks. 2014. <u>https://ieeexplore.ieee.org/abstract/document/6757897</u>
- 5. Accuracy of Perceptron based beamforming for embedded smart and MIMO antennas. 2016. https://ieeexplore.ieee.org/document/7803215
- 6. CiFi: Deep convolutional neural networks for indoor localization with 5 GHz Wi-Fi. 2017. https://ieeexplore.ieee.org/abstract/document/7997235
- 7. Direction of arrival estimation for smart antenna in multipath environment using convolutional neural network. 2018. https://onlinelibrary.wiley.com/doi/abs/10.1002/mmce.21282
- 8. Reinforcement learning-based waveform optimization for MIMO multi-target detection. 2018. https://ieeexplore.ieee.org/document/8645304/

## THE VALUE OF PERFORMANCE.



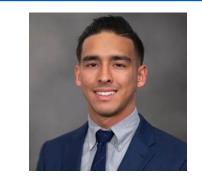
#### Abstract



• With the emergence of more complex space systems, there is a strong need to optimize network and data link capacities that will work in concert with cognitive radios to manage the spectrum effectively. A cognitive antenna for this matter will be an environmentally aware antenna that can manage bandwidth, beam direction and directivity, equivalent isotropically radiated power (EIRP), and nulling to improve spectral, spatial, and temporal resources and complement cognitive radio technology. We propose to survey different artificial intelligence and machine learning techniques for the purposes of aggregating data from various sources (e.g. cognitive radio, environment, instrumentation, etc.) that can be utilized to facilitate smart decisions about how to configure a complex phased array to ensure threshold link performance is achieved. Furthermore, we will explore where the cognition controlling algorithms should reside within the highly integrated space system to yield higher communications performance benefits.

### **Author Biographies**





**Samuel Vineyard** received his B.S. in Electrical Engineering at the University of California, San Diego (UCSD) in 2017 with an emphasis on Machine Learning. He is currently a Systems Engineer for the Communications and Signals and Intelligence (Comms & SIGINT) Operational Unit (OU) at Northrop Grumman. His work has focused on developing advanced low Technology Readiness Level (TRL) communications and networking systems for applications spanning across ground, air, underwater, and space domains. He consistently supports Comms and SIGINT OU proposals for next generation military systems.



**Suzanna LaMar** received her B.S. in Electrical Engineering at the University of San Diego, CA in 2001. She received her M.S. in Electrical Engineering with an emphasis in Signal and Image Processing at the University of California, San Diego (UCSD) in 2006. She is currently the Chief Engineer for the Communications and Signals and Intelligence (Comms & SIGINT) Operational Unit (OU) at Northrop Grumman supporting early technology developments and maturation. She has extensive experience in radio frequency engineering and network communications where her work has concentrated on research and development projects for advanced military systems. Suzanna LaMar is an Northrop Grumman Technical Fellow.



**Todd Gillette** received his B.S. in Engineering and B.A. in Computer Science at Swarthmore College in 2003. He received his Ph.D. in Neuroscience from George Mason University in 2015 with a focus on informatics applied to neuronal morphology. Todd recently graduated the Northrop Grumman Future Technical Leader (FTL) program, having provided systems engineering support on the F-35 CNI and Comms & SIGINT OU proposals and IRAD, and is now heading to Baltimore to apply machine learning and cognitive approaches with CIMS and Advanced Intelligent Systems (AIS). Todd is a certified INCOSE ASEP.