Using Cognitive Communications to Increase the Operational Value of Collaborative Networks of Satellites

Ryan B. Linnabary
Dept. Elec. & Comp. Eng.
The Ohio State University
Columbus, OH, USA
linnabary.24@osu.edu

Andrew J. O'Brien
Dept. Elec. & Comp. Eng.
The Ohio State University
Columbus, OH, USA
obrien.200@osu.edu

Graeme E. Smith
Dept. Elec. & Comp. Eng.
The Ohio State University
Columbus, OH, USA
smith.8347@osu.edu

Christopher Ball
Dept. Elec. & Comp. Eng.
The Ohio State University
Columbus, OH, USA
ball.51@osu.edu

Joel T. Johnson
Dept. Elec. & Comp. Eng.
The Ohio State University
Columbus, OH, USA
johnson.1374@osu.edu

***Abstract*—Distributed satellite constellations utilizing networks of small satellites will be a key enabler of new observing strategies in the next generation of NASA missions. While it is quickly becoming feasible to establish communication networks among small satellites, a key question is how these networks can be best utilized to achieve objectives. While small satellite instruments are becoming more capable, they are still resource constrained (i.e. power, data, scanning systems, etc.); therefore, adaptive instruments that intelligently adjust parameters on the fly are key for increasing operational value within these constraints. In this context, the purpose of collaborative communication among small satellites is to achieve system-level adaptivity. This dramatically increases the complexity of the control algorithms and decision space in which the small satellites communication networks must operate. We postulate that cognition in the high-level collaborative communication is one approach to both achieve autonomy and to address this complex control space. In this paper, we investigate concepts for how machine learning (ML) algorithms can be utilized in the high-level decision making of a communication system in a distributed satellite mission. This paper will show cognitive communication model with ML and some example case study results.**

***Keywords*—Distributed Satellite Missions, Autonomous Systems, Sensor Network, Sensor Web, OSSE**

I. Introduction

It is envisioned that NASA's future space systems will be composed of large, inhomogeneous networks of small satellites and autonomous platforms [1]. These resource constrained systems, carrying an array of different instruments, will be expected to operate autonomously and collaboratively to achieve mission and science goals. Unfortunately, current and near-future inter-satellite communications are highly constrained in terms of link availability, reliability, power and bandwidth. Although future technologies (such as free space optical links) may alleviate some constraints, it is expected that future instruments will rapidly expand in both data volume and sensor reconfigurability [2]. In this way, it is not sufficient to simply increase the capabilities of the communication links. Rather, it is also necessary to improve the complex decision making that communication systems perform, such as deciding when to transmit, what information is valuable to nodes of the network, and how to adapt local operations following the reception of new information.

Recently, cognitive space communication algorithms have been proposed as a solution to address the complexity of future inter-satellite communication systems [3]. Typically, these cognitive algorithms have tried to address communications at a low level and include decision making regarding modulation, power and bandwidth, and error rate [4], [5]. However, it is reasonable to expect that cognition may also offer an improvement in the complex, higher level decisions of communication in the context of mission and science objectives. At this level, cognition is applied to the operation of the network with the decision making primarily influenced by the constraints of the space communication network links.

In this work, we show results of simulation studies to explore the advantages that cognition could offer for collaborative small-satellite networks. Under a NASA Advanced Information System Technology program, we are currently developing an open-source C++ library for the simulation of autonomous and collaborative networks of adaptive sensors [6]. This library and accompanying utilities allow for the efficient simulation of networks of satellites with realistic constraints in communication, power, and measurements. A key focus of this software is the simulation of sensors that operate adaptively. Adaptive sensors must make intelligent

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decisions regarding their configuration based on their own measurements as well as the measurements provided by other sensors in a network. However, the extreme complexity of the decision space makes the development of optimal decision-making systems very difficult. Thus, an approach based on cognition could offer an appealing solution. We investigate how our simulation tools could be useful for production of large training datasets that capture the operation of collaborative, adaptive networks of small satellites. We then investigate how such a dataset could be combined with machine learning techniques to train neural networks that could make intelligent decisions about when and what to communicate. Results from our investigation will be presented, and the applicability of these methods to future cognitive space communication will be discussed.

II. Collaborative Networks Of Adaptive Sensors

Satellite sensor constellations are now feasible. Current constellations are managed in simple ways with ground contacts. Future constellations operate more autonomously with inter-sat communicaitons

The remote sensing community anticipates significant demand for simulation tools as low earth orbit (LEO) small satellites become a common platform for observing system missions. This research team has been tasked with developing simulation tools capable of addressing the challenging problems discussed in Section I. The proposed solution has three main components: resource management, adaptive sensor hardware, and collaborative networking. These components may be combined to produce high-fidelity simulations for validating adaptive sensor designs.

Satellites will carry adaptive sensors. Require ability to make decisions about how to adjust sensor parameters based on own measurements. more complex to adjust parameters based on entire constelations

Adaptive sensor networks work together in the following way: a sensor obtains a measurement, quantifies the measurement's science value and system resource cost, predicts the network state and data model, and shares this information with network members. Network members adapt their behavior or sensor hardware in response to this new information. The development process has revealed opportunities for expansion and improvement involving cognitive communication and machine learning.

Collaboration between satellites enables full utilization of adaptivity. represents the highest complexity of sensor network. low TRL. Difficult to grasp due to complexity. decision making, reacting to environment and very large space of information. Can cognition be applied here?

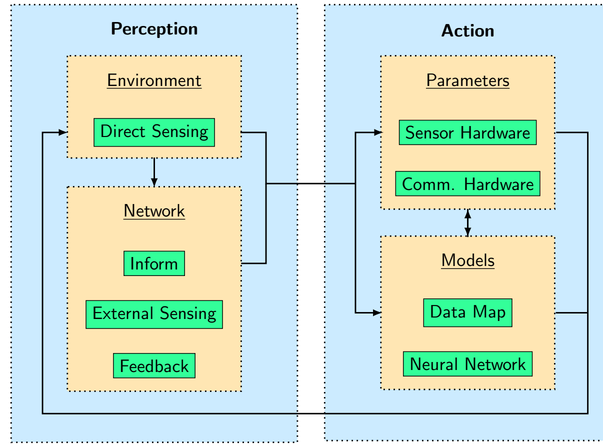


Fig. 1. Cognitive Communications Model

III. Cognition and High-Level Communications

A. Cognitive Communications

Since many interpretations exist, we begin with defining what is meant by Cognitive Communications. *Cognition* refers to the act of selecting and carrying out actions based on both specific goals and perception of an external environment. Cognition necessarily includes learning from past experiences and interactions with the environment. Thus, a *cognitive entity* is capable of taking action based on its goals and perception of the environment, potentially learning from the result of its action. It is an intelligent entity that posesses perception, learning, reasoning, and making decisions [7]. *Cognitive Communications* are communications whose operations are in some way dependent on cognition.

Thus far, research into cognitive communication for satellite systems has been predominantly focuses on low-level communication aspects. (Insert references and descriptions of conference papers from past CCAA). However, cognition can also be applied to the higher-level aspects of a communication system. For example, cognition could be applied to the intelligent routing of information within an autonomous satellite sensor network [7]. Alternatively, this routing could establish a collaborative improvement in mission science return and achieve, in effect, a system level adaptivity in response to events. Thus, consideration of collaboration to '"adaptive remote sensing'" and feedback are added to traditional inter-satellite communication. A model for cognitive communications is illustrated in Fig.1, a perception-action cycle for proposed autonomous networks.

(Summary of different methods for dealing with this problem. Can ML help?)

B. Machine Learning and Cognitive Communications

Machine learning provides computers the ability to learn without being explicitly programmed. Such intelligent machines are capable of accurately predicting and classifying new data. Computers can be programmed to learn autonomously with or without supervision, and often require significant quantities of training data and careful adjustment of model parameters. These techniques are useful for the problems which: require many manual adjustments or long lists of rules; operate in a fluctuating environment; need to process a large amount of data; or have no known optimal solution.

Machine learning techniques are currently being applied in the development of adaptive hardware, resource optimization, and other areas of sensor network design. An opportunity exists to use machine learning to optimize information flow within a collaborative network of satellites. Improvements would increase communications efficiency by increasing the value of data contents and reducing operational resource consumption.

All of the common machine learning algorithms apply to optimization of high-level communication parameters. Regression tasks enable satellites to autonomously adjust parameters for communication, sensing, and on-board data processing. Classification of network nodes based on proximity and capabilities could increase efficiency by informing antenna direction or temporal scheduling. This research involves the application of new and existing machine learning algorithms. Existing algorithms are widely available as third-party Python modules, and will be discussed later in Section IV. Custom algorithms are developed for the C++ library.

- Example references of how it has been applied

- Generation of training data, training of the NN, application of the NN to the system. What are input and outputs. What are the steps? List of steps in proposed procedure if needed

IV. Sensor Network Simulations to Support Machine Learning Research

Research in applying machine learning to sensor networks will rely on simulations to validate algorithms both deployed on spacecraft and on the ground. Simulations must provide the means for basic cognitive communication as well as the production of training data for post-processing by neural networks. Training data should include simulation variables which are suspected of correlation to the parameter being optimized. Variables may capture time-series data involving satellite position, health, communication hardware details, sensor hardware details, network connectivity, or other similar parameters.

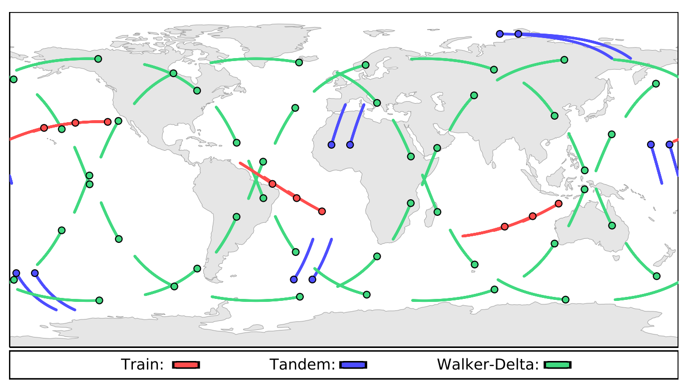
A software tool-set COLLABORATE is under development which is capable of producing the described training data. The toolset has two main components: first, a C++ development library for observing system simulation experiments; and second, a Python visualization and analysis package for post-processing of data. The project is published to a Git repository under the GPLv3.0 license.

The COLLABORATE library offers a number of unique features valuable to future observing system simulation experiments. At its core, it is a physics engine for satellite position, velocity, and attitude. Power and RF accessories may be attached to satellites and individually oriented. The next level involves rapid constellation design. Standard orbit models described by two-line-element (TLE) sets are provided, copied, and modified to generate novel and interesting constellation patterns. Examples are illustrated in Fig.2(a).

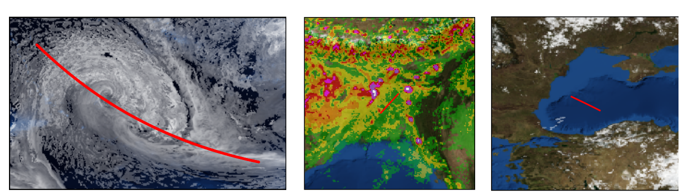
Sensor hardware is attached to satellites as an interface to truth data (NetCDF Nature Run data). This provides a custom modeling environment for real sensor hardware and enables heterogeneous sensor constellations with different capabilities. As a satellite orbits, its pointing vector intersects Earth's surface or an atmospheric layer and samples the underlying data, as shown in Fig.2(b-d).

COLLABORATE is named for its ability to manage collaborative networks of satellites. Its implementation focuses on the high-level communication decision space previously discussed. The library employs, in addition to standard C++ components, advanced data structures including trees and graphs to execute predictive route-finding algorithms for efficient communications. For example, line-of-sight wireless channels are captured in a graph, as illustrated in Fig.3(a), the minimum spanning tree.

A predictive scheduling algorithm is illustrated in Fig.3(b). Satellite "A" measures cloud depth in the Pacific Ocean (blue line). It then predicts the arrival of a follow-up satellite and relays a message through satellites "B" and "C" to queue "D" for a measurement with a different sensor (red line). Signifi-

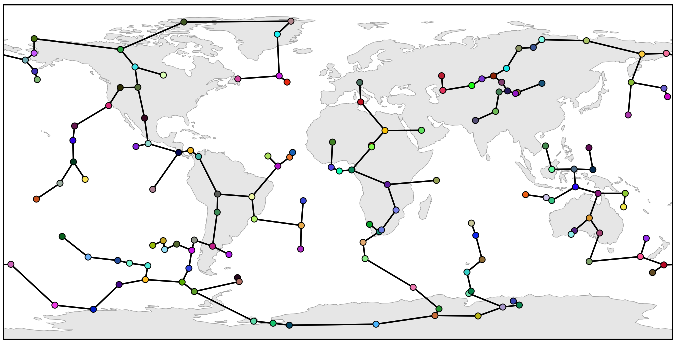


(a) Various constellations defined by orbit patterns

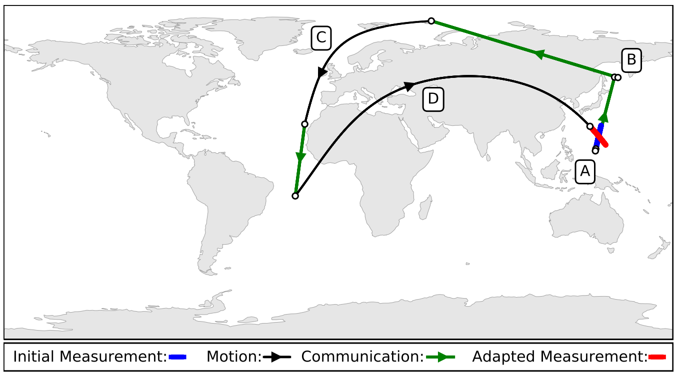


(b) Cloud Depth (c) Precipitation (d) Optical Images

Fig. 2. Simulated remote sensing

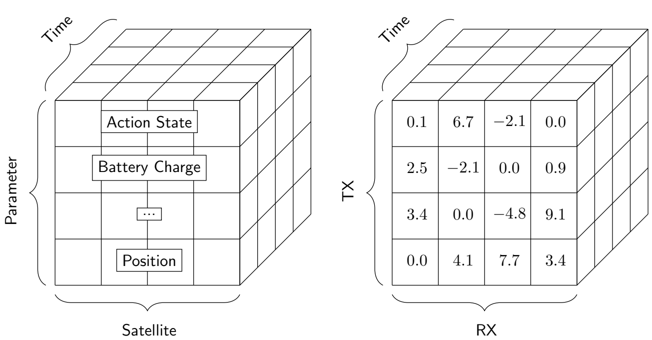


(a) Instantaneous network graph structure (minimum spanning tree)



(b) Collaborative sequence in time

Fig. 3. Simulated collaborative networks



(a) Satellite parameter data (b) Network parameter data

Fig. 4. Simulation training data formats

cant work has been done to optimize this algorithm, because it is the main consumer of CPU time and is run regularly in simulation to find routes. It is also the foundation for deployed cognitive communications, as discussed in Section V.

Presently, the included algorithms are iterative and often take minutes to conclude. It may be possible to reduce run-time or optimize routes based on alternative parameters using machine learning. An option is to replace these algorithms with predictive neural networks for advanced regression or classification algorithms. COLLABORATE facilitates this by producing data in standard formats for post-processing.

The software logs simulation data to files accessible by external machine learning tools. COLLABORATE was developed around simple data formats for portability and to promote development of custom analysis tools. Primarily, data is serialized and written to binary files. These formats are well documented and easy to parse in Python or other scripting languages. Included Python packages understand the data formats and can read and store the data for later use as Numpy or Pandas data structures. Examples include time-series data frames or network adjacency matrices (weighted and unweighted). Fig.4 shows several common data structures in memory.

Python scripts are provided not only for receiving simulation data at a low level, but also many high level analysis tasks. In fact, all figures in this document were produced using the tools provided by the library. Primary third-party packages used include the following: Numpy, Pandas, Cython, NetCDF4, Matplotlib, Cartopy, Scikitlearn, TensorFlow, and SciPy. These enable post processing for plots and animations or to train machine learning algorithms. Numpy and Pandas provide powerful linear algebra and statistics operations. Cartopy provides extensive map projections and transformations which support visualizing satellite positions and truth data. Machine learning algorithms are available in the Scikitlearn and Tensorflow packages, which interface well with Numpy and Pandas structures.

For example, satellite parameter data (Fig.4(a)) is plotted in Fig.5 to expose and potentially exploit correlations. Several of these seem strongly correlated and many are also periodic. Potential high-level communications optimizations may involve predicting when a satellite has the most visible neighbors (available line-of-sight links). An algorithm for power management scheduling may use the instantaneous charge or power to plan efficient sensor operation.

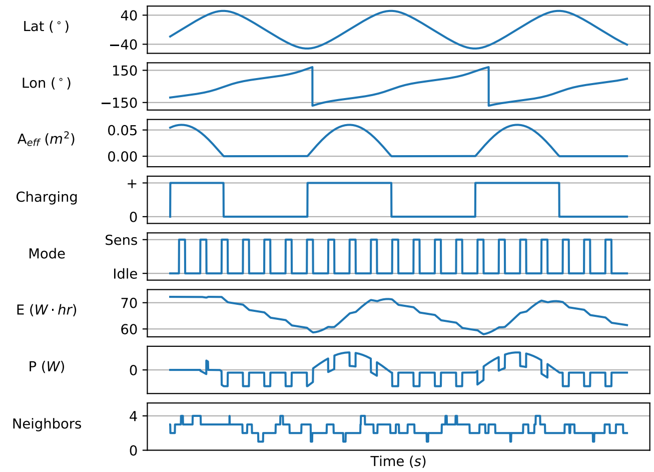


Fig. 5. Visualized simulation data

V. EXAMPLE CASE STUDIES

The following examples demonstrate cognitive communications and machine learning techniques applied to software simulations. First, parametric regression is automated using the COLLABORATE network feedback algorithm. This simulates deployed machine learning in a realistic observing system. Second, satellites are classified based on line-of-sight proximity. This demonstrates the utility of COLLABORATE simulation data for training external machine learning models.

A. *Cognitive Feedback For Autonomous Parameter Regression*

Section IV shows that COLLABORATE provides a network algorithm for predicting optimal routes, such as the one illustrated in Fig.3(f); this can also be used to predict a path for feedback to the original satellite. A single feedback cycle is shown in Fig.6(a). In this plot, a cognitive satellite travels from South America over the Atlantic and senses data over Africa (blue line). Internal processing reveals that the science value of a follow-up measurement exceeds expected resource costs, so the satellite predicts the arrival of another sensor platform. A message is forwarded through the network over the Pacific to queue the next measurement. After a follow-up measurement, data is fed back to the original satellite over the Middle East and China. The contents of this feedback message inform corrective action by the cognitive satellite.

Science value optimization is demonstrated by a 24-hour simulation where this feedback cycle is repeated 75 times. In this simulation, the cognitive satellite performs a regression task to discover the correlation between cloud depth and precipitation. The top plot in Fig.6(b) illustrates regression of the target parameter (cloud depth threshold for non-zero precipitation). Initially the threshold is set to 0 meters and the cloud radar requests follow-up precipitation measurements indiscriminately. For the first 16 regression cycles in the bottom plot of Fig.6(b), 20 percent of the precipitation sensors measured non-zero precipitation. At 16 cycles the satellite begins adjusting the threshold, which converges to a value of 65 meters after 32 cycles. The new threshold improves operational science return by increasing the number of non-zero precipitation measurements to 50 percent.

B. *Spectral Clustering Using Simulated Network Data*

Simulation data described in Fig.4(b) is produced by a simulation and used to train a machine learning (classification) algorithm. The data contains a time series of adjacency matrices with edge weights equal to line-of-sight distances between nodes. A single frame of this data is inverted and normalized to produce an affinity matrix suitable for ScikitLearn's SpectralClustering algorithm. This algorithm identifies normalized cuts in the graph and separates nodes into groups. Fig.7(a-c) show how a graph is sorted and reduced to isolate groups of nodes based on proximity. Fig.7(d) shows the 15 clusters using actual satellite positions.

COLLABORATE currently supports one-to-one communication, but future network schemes will require one-to-many links and will likely employ clustering as a single part of its optimization routine. For example a satellite may strategically orient its antenna toward the center of its cluster, maximizing signal strength for its immediate neighbors.

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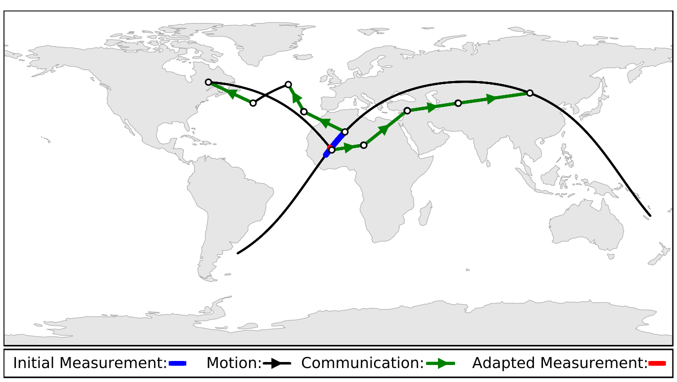
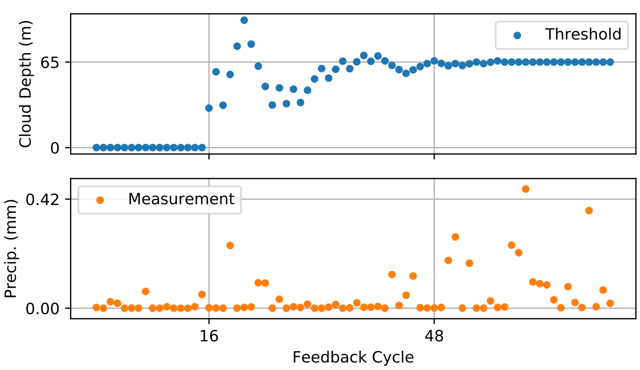
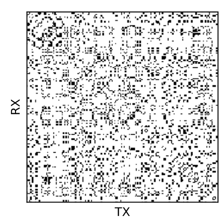


(a) Feedback route

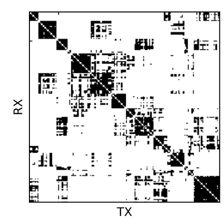


(b) Autonomous parametric regression for data correlation threshold

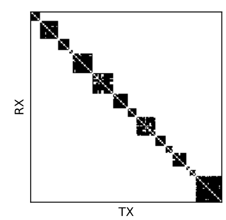
Fig. 6. Cognitive communications feedback



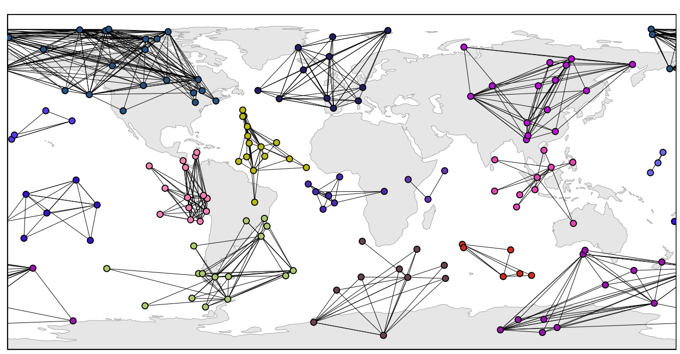
(a) LOS Matrix



(b) Sorted Clusters



(c) Isolated Clusters



(d) Map of isolated clusters

Fig. 7. Spectral clustering by k-means classification

VI. Summary And Next Steps

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