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

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***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 critical question is how these networks can be best utilized to achieve objectives. Small satellite instruments are becoming more capable, but they are still resource constrained (i.e. power, data, scanning systems, etc.). Adaptive instruments that intelligently adjust parameters on the fly are essential for increasing operational value within these constraints, and the primary purpose of collaborative communication among small satellites is to achieve system-level adaptivity. This could dramatically increase the complexity of the control algorithms for small satellite communication networks. Application of cognitive communication is one promising method to address this problem. In this paper, we discuss our recent investigations into how machine learning (ML) algorithms can be utilized in the high-level decision making of a communication system in a distributed satellite mission.**

***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].

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 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 data-sets that capture the operation of collaborative, adaptive networks of small satellites. We then investigate how such a data-set could be combined with machine learning techniques to train neural networks that could make intelligent decisions about when and what to communicate. The applicability of these methods to future cognitive space communication will be discussed.

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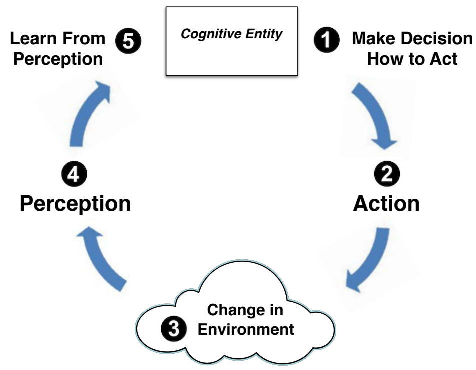


Fig. 1. Fundamental process of cognition, the perception-action cycle.

II. Identifying a Role for Cognition in High-Level Communications

Cognition refers to the act of selecting and carrying out actions based on both specific goals and perception of an external environment. Key to cognition is the perception-action cycle depicted in Figure 1. 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 possesses perception, learning, reasoning, and making decisions [7]. *Cognitive Communications* are communications whose operations are in some way dependent on cognition.

Research into cognitive communication algorithms for satellite systems have focused on communications at a low level, including decision making regarding modulation, power, bandwidth, and error rate. For example, on-line machine learning was used to optimize the selection of of software-defined radio parameters in [4]. Cognitive digital beamforming has also been applied to satellite communication [5]. However, cognition can also be applied to the higher-level aspects of a communication system, such as the intelligent routing of information within an autonomous satellite sensor network [7].

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. Communication networks within distributed small satellite constellations will enable collaborative operations, and, when these satellites are equipped with adaptive sensors, collaborative communications will enable system-level adaptivity.

In order to illustrate this, consider an example sequence of events shown in Figure 2. In this scenario, 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). After the second measurement is made, information is fed back to the originating satellite (Satellite "A"), so it can learn about how valuable the information was and how successful the communication route over the network was.

Figure 3 shows a depiction of the perception-action cycle as it applies to our scenario of interest. Here, a small satellite serves as the cognitive entity. The action it takes is to determine what information to send and what route to try to send it on. This action influences the rest of the small satellite constellation by causing them to adjust their sensors and make measurements in an improved manner. The information about this influence is fed back to the original satellite so that it can learn from this reaction.

The problem that prevents a practical implementation of the model shown in Figure 3 is that the decision-making and learning processes is very difficult to model and design. This is especially true when considering the significant uncertainty at any given moment given the state of the constellation and the communication routes available. Machine Learning (ML) is one approach to overcome this problem. Machine learning techniques are currently being applied in the development of adaptive hardware, resource optimization, and other areas

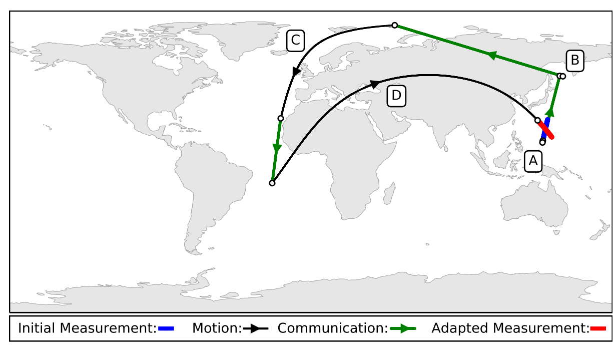


Fig. 2. Example sequence of collaboration between satellites in a constellation.

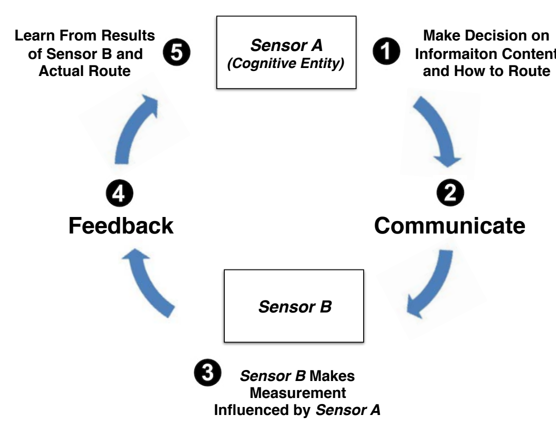
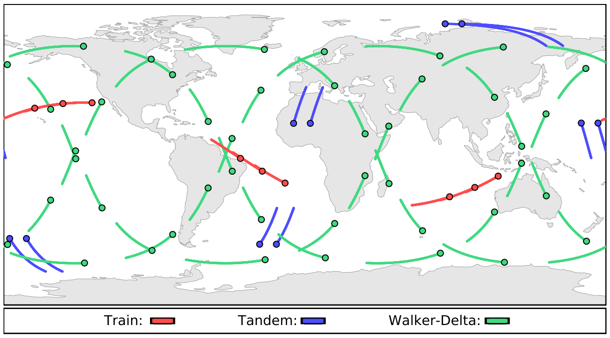
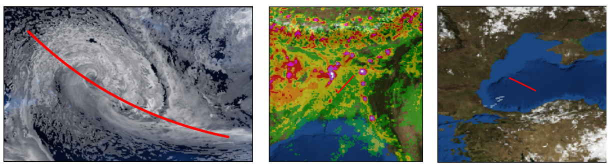


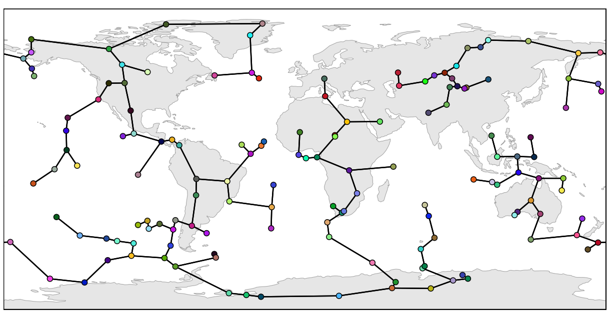
Fig. 3. Perception-action cycle of cognition as applied to collaborative communications between satellites.



(a) Various constellations defined by orbit patterns



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



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

Fig. 4. COLLABORATE software features

of sensor network design. An opportunity exists here 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.

The most common machine learning categories (i.e. regression and classification) can be applied to high-level network management tasks. 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.

III. Sensor Network Simulations to Support Machine Learning

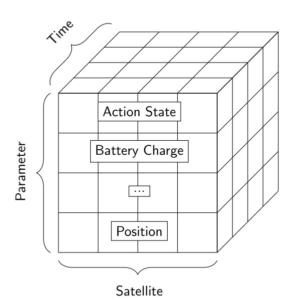
A software tool-set COLLABORATE is under development which is capable of producing the training data for ML algorithms. The tool-set has two main components: first, a C++ development library for observing system simulation experiments; and second, a Python visualization and analysis package for post-processing 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 Figure 4(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 Figure 4(b-d).

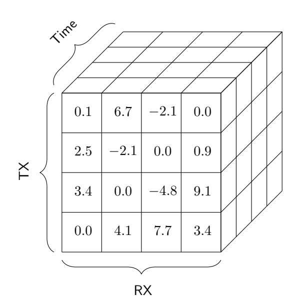
COLLABORATE is named for its ability to manage collaborative networks of satellites. Its implementation focuses on the high-level communication decision space discussed previously. The library employs, in addition to standard C++ components, advanced data structures including trees and graphs to execute predictive route-finding algorithms for efficient communications. For example, line-of-sight wireless channels are captured in a graph, as illustrated in Figure 4(e), the minimum spanning tree.

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). Figure 5 shows several common data structures in memory; one to store satellite parameters; and another for network structures.

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



(a) Satellite parameter data



(b) Network parameter data

Fig. 5. Simulation training data formats

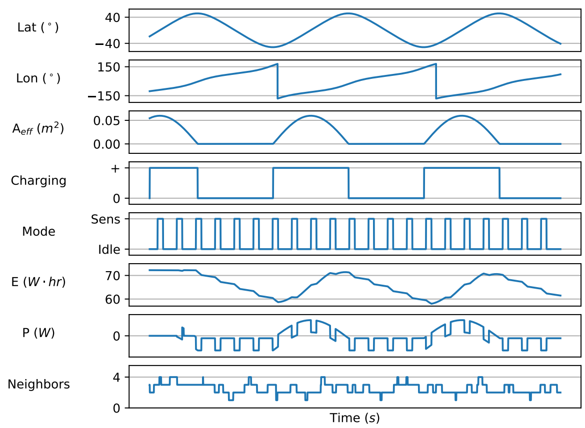


Fig. 6. Example parameters versus time from simulation data

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 (Figure 5(a)) is plotted in Figure 6.

IV. 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.

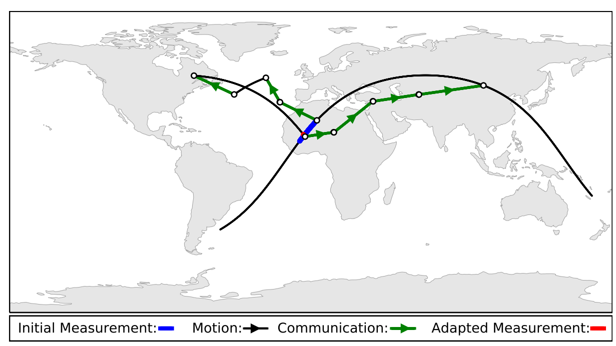
A. Cognitive Feedback For Autonomous Parameter Regression

Section III shows that COLLABORATE provides a network algorithm for predicting optimal routes, such as the one illustrated in Figure 2; this can also be used to predict a path for feedback to the original satellite. A single feedback cycle is shown in Figure 7(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.

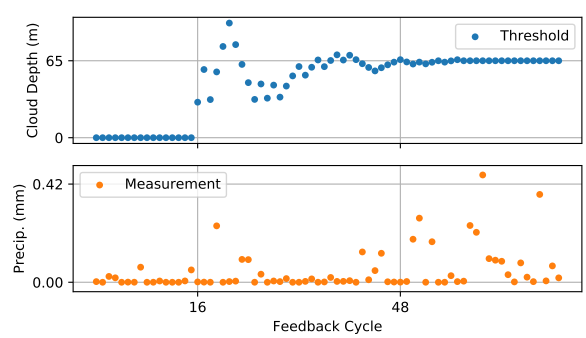
Science value optimization is demonstrated by a 24-hour simulation where this feedback cycle is repeated 75 times. In this simulation, the cognitive satellite performs a regression task to discover the correlation between cloud depth and precipitation. The top plot in Figure 7(b) illustrates regression 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 Figure 7(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 Figure 5(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. Figure 8(a-c) show how a graph is sorted and reduced to isolate groups of nodes based on proximity. Figure 8(d) shows the 15 clusters using actual satellite positions.

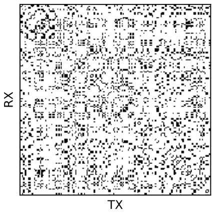


(a) Feedback route



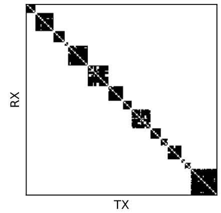
(b) Autonomous parametric regression for data correlation threshold

Fig. 7. Cognitive communications feedback

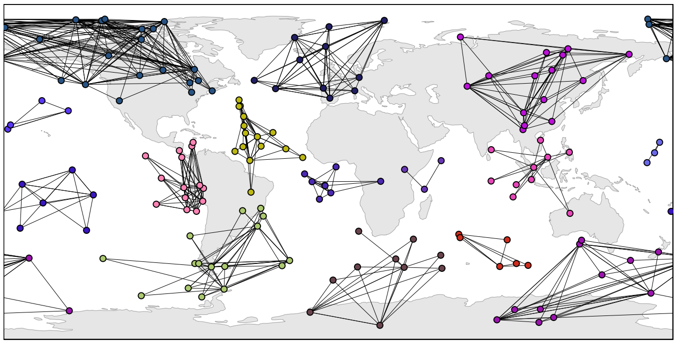


(a) LOS Matrix

(b) Sorted Clusters



(c) Isolated Clusters



(d) Map of isolated clusters

Fig. 8. Spectral clustering by k-means classification

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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