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. Small satellite instruments are becoming more capable, but are still resource constrained (i.e. power, data, scanning systems, etc.) in many situations. On a system scale, the primary purpose of collaborative communication among small satellites is to achieve system-level adaptivity. Collaborative communications however may also dramatically increase the complexity of the control algorithms for small satellite communication networks. Application of cognitive communication methods 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. We performed simulation studies to explore how the perception-action cycle could be applied to a collaborative small-satellite networks. To support this, we are using a recently developed open-source C++ library for the simulation of autonomous and collaborative networks of adaptive sensors.**

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

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 both the data volume and sensor reconfigurability of future instruments will expand [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 complexity of the decision space makes the development of optimal decision-making systems difficult. Approaches based on models for "cognition" offer an appealing approach to this challenge. 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 is also discussed.

This research was sponsored by the NASA Advanced Information Systems Technology Program NNH16ZDA001N-AIST.

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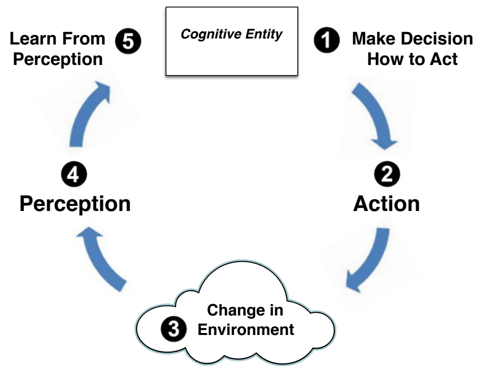


Fig. 1. Fundamental process of cognition, the perception-action cycle.

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 Fig. 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 results of its actions. The resulting entity is an intelligent system that possesses perception, learning, reasoning, and decision making capabilities [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 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 Fig. 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 cue “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.

Fig. 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.

A problem that prevents practical implementation of the model shown in Fig. 3 is that the decision-making and learning processes are 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 address this problem. Machine learning techniques are currently being applied in the development

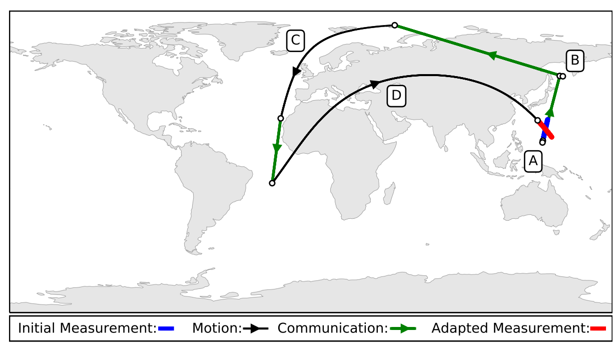


Fig. 2. Example sequence of collaboration between satellites in a constellation.

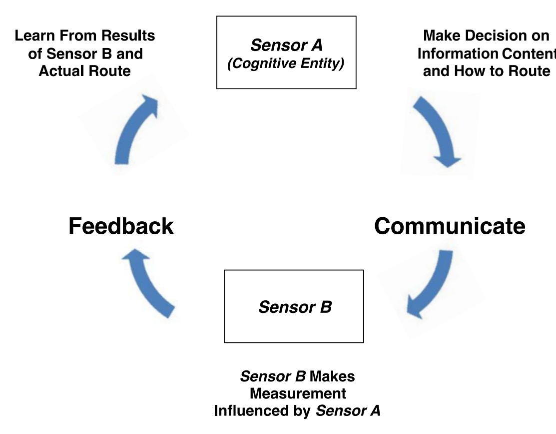


Fig. 3. Perception-action cycle of cognition as applied to collaborative communications between satellites.

of adaptive hardware, resource optimization, and other areas of sensor network design. An opportunity exists in satellite sensing applications to use machine learning to optimize information flow within a collaborative network of satellites. Improvements would increase communications efficiency by increasing the value of the data obtained and by 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 adjust parameters autonomously for communication, sensing, and on-board data processing. Further classification of network nodes based on their proximity and capabilities could further increase efficiency by informing antenna pointing or temporal scheduling decisions.

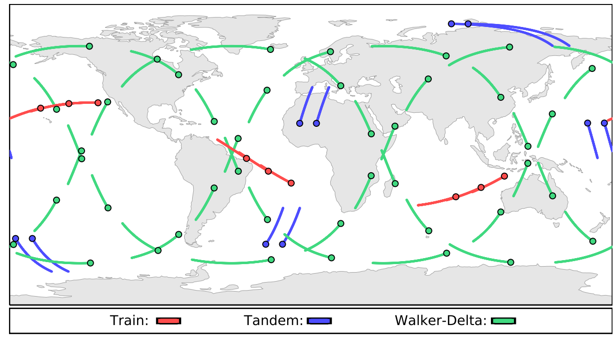
III. Sensor Network Simulations to Support Machine Learning

A software tool-set COLLABORATE is under development which is capable of producing the required training data to implement ML algorithms for these purposes. 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.

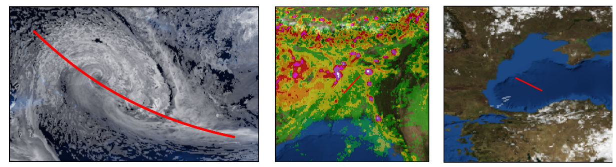
The COLLABORATE library offers a number of unique features valuable to future observing system simulation experiments. At its core, it is a prediction engine for satellite position, velocity, and attitude that is coupled to associated spacecraft power and communication accessories that may be attached 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 constellation patterns. Examples are illustrated in Fig. 4(a). Finally, sensor hardware is attached to satellites as an interface to geophysical datasets from Earth systems models (e.g. NetCDF Nature Run data). This provides a custom modeling environment for realistic sensor hardware and enables heterogeneous sensor constellations in which each node possesses distinct sensing 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. 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 Fig. 4(e), the minimum spanning tree.

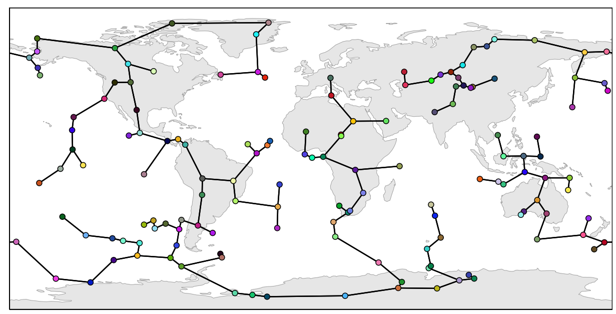
The software logs simulation data to files accessible by external machine learning tools. COLLABORATE was developed around simple data formats (typically data is serialized



(a) Various constellations defined by orbit patterns



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

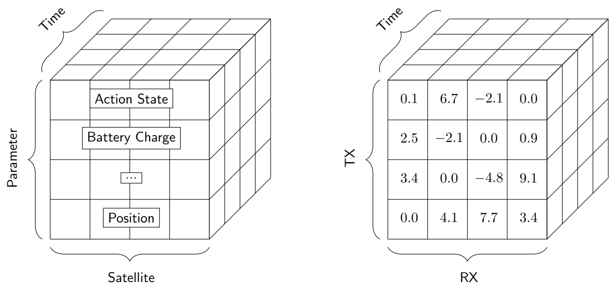


(e) Instantaneous network graph structure (minimum spanning tree)

Fig. 4. COLLABORATE software features

and written to binary files) for portability and to promote development of custom analysis tools. These formats are well documented and easy to parse in Python or other scripting languages. The included Python packages 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. 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 for high level analysis tasks (note that all figures in this document were produced using the tools provided by the library). Third-party packages used include: Numpy, Pandas, Cython, NetCDF4, Matplotlib, Cartopy, Scikitlearn, TensorFlow, and SciPy. These tools enable post processing for plots and animations or to train machine learning algorithms. In particular, Numpy and Pandas provide powerful linear algebra and statistics operations, while Cartopy provides map projections and transformations to 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 struc-



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

Fig. 5. Simulation training data formats

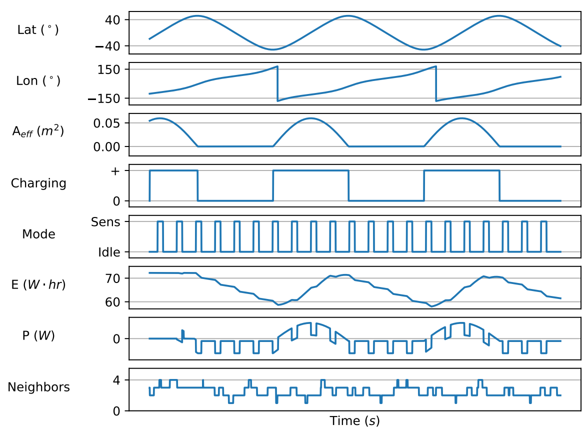
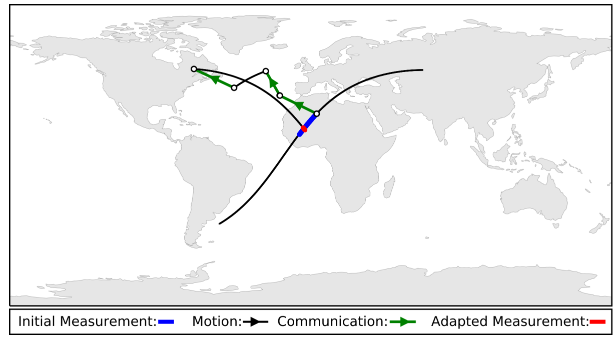
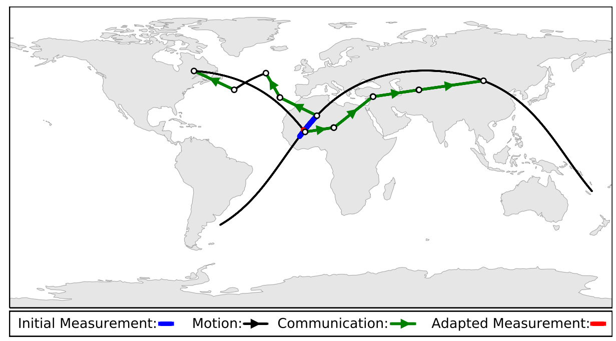


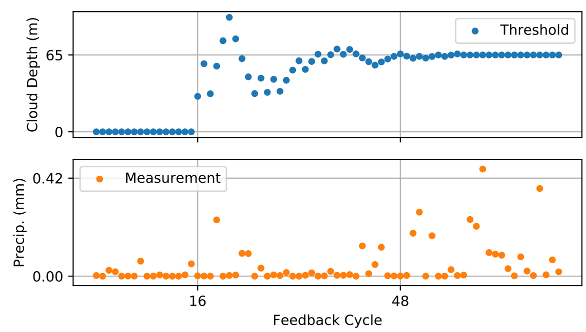
Fig. 6. Example parameters versus time from simulation data



(a) Forward route



(b) Feedback route



(c) Autonomous parametric regression for data correlation threshold

Fig. 7. Cognitive communications feedback

tures. Satellite parameter data (Fig. 5(a)) is plotted in Fig. 6 as an example, which shows that several operational parameters are strongly correlated and have a periodic variation with orbit position. High-level communications optimizations may involve this data for example to predict when a satellite has the greatest number of visible neighbors (i.e. available line-of-sight links). Similarly, an algorithm for power management scheduling may use the instantaneous charge or power to plan efficient sensor operations.

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 deploying 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

The first example shows how collaborative communication between satellites can form a cognitive perception-action cycle that can improve science measurements. A simulation was run containing hypothetical small satellite constellations of cloud radars and precipitation radar sensors. Here we assume these constellations have been designed with a compatible inter-satellite line-of-sight communication mechanism.

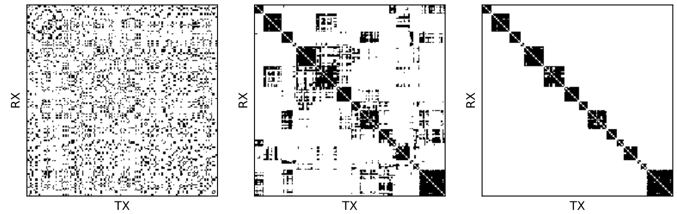
The scenario of interest is shown in Fig. 2(a). Here a small satellite travels from South America over the Atlantic and senses data over Africa (blue line). The satellite predicts the arrival of another satellite over the same area in the future. Internal processing on the first satellite estimates that the science value of a follow-up measurement exceeds expected resource costs associated with communicating that information, so a message is forwarded through the small satellite network over the Pacific to the target satellite. Since the first satellite has knowledge of the constellation configuration, it can estimate that it is likely the information will arrive at the target satellite in sufficient time. The target satellite then optionally uses this information to adapt its sensor and queue the next measurement over the same area. After the second measurement is made, the second satellite is able to quantify the value of this measurement. Next, to complete the perception-action cycle, information must be fed back to the first satellite. This information involves the improvement that was achieved. Fig. 2(b) shows how data is fed back to the original satellite over the Middle East and China.

Science value optimization is demonstrated by a 24-hour simulation where this feedback cycle is repeated 75 times. In this simulation, the sensing goal focuses on the measurement of precipitation, so that methods to inform other satellites of the presence of precipitation are of interest. In this simulation, a first satellite that is capable of measuring cloud depth (but not precipitation) is used to provide guidance to a sensor on a differing platform that measures precipitation. In the simulation, the cloud-depth measuring sensor first requests follow-up measurements from the precipitation sensor in all cases. However, through knowledge of the outcome of the follow up measurement in each case, the cognitive satellite performs a regression task to discover the correlation between cloud depth and precipitation. The top plot in Fig. 7(c) illustrates regression of the target parameter (cloud depth threshold for non-zero precipitation). The initial value of 0 meters represents the case when the cloud depth sensor requests follow up precipitation measurements indiscriminately. For the first 16 regression cycles in the bottom plot of Fig. 7(c), 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.

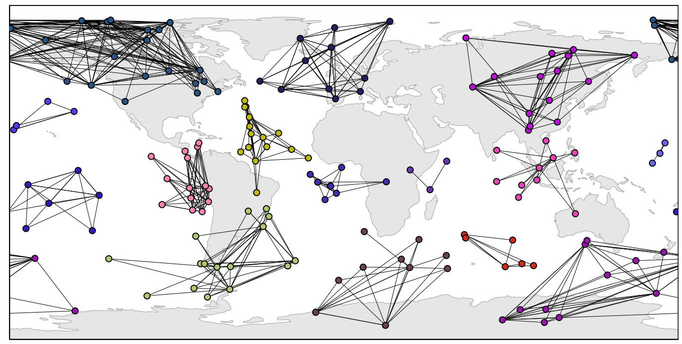
B. Spectral Clustering Using Simulated Network Data

As an additional example, the network parameter data described in Fig. 5(b) was obtained from 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 the 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. 8(a-c) show how a graph is sorted and reduced to isolate groups of nodes based on proximity. Fig. 8(d) shows the 15 clusters using actual satellite positions, and demonstrates the success of the Machine Learning algorithm in identifying appropriate groupings of nodes to optimize network communications.

The results of these studies demonstrate the potential advantages of multi-platform collaborative sensing, as well as the need for robust simulation tools to achieve robust performance. The Machine Learning approach examined also shows many of the properties of a cognitive entity in refining and optimizing measurement strategies. 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



(a) Possible Channels (b) Sorted Clusters (c) Isolated Clusters



(d) Map of isolated clusters

Fig. 8. Spectral clustering by k-means classification

satellite may strategically orient its antenna toward the center of its cluster, maximizing signal strength for its immediate neighbors. Development of the library will continue with the goal of advancing collaborative sensing constellations into future remote sensing practice.

V. Summary & Next Steps

This paper has introduced our current work on applying cognitive communications to the information flow in a collaborative small satellite network. Future small satellites will likely carry adaptive instruments that intelligently adjust parameters on the fly, and it is our belief that the primary purpose of collaborative communication among small satellites is to achieve system-level adaptivity with such instruments. Our approach is to use custom simulation software to investigate cognition as one means of overcoming the complex decision space that such small satellites must operate within. Going forward, we hope to expand these simulations with larger and more compelling usage cases.

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