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

Abstract

Future Earth-observing systems will involve distributed missions of autonomous and heterogeneous spaceborne sensor networks. Future sensor webs will occupy a more complex decision space but will be capable of adaptive decisions and collaborative networking. These capabilities must be utilized to increase a network's operational value and to reduce human involvement in high-level communications decisions. Developing this technology may be greatly accelerated by machine learning techniques and cognitive communications algorithms. The following research describes the development and analysis of simulated observing-systems which employ a cognitive communications model, and concludes with an analysis of simulation results, their implications, and potential for extension or improvement.

I. INTRODUCTION

It is envisioned that NASA's future space systems will be composed of large, inhomogeneous networks of small satellites and autonomous platforms. 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. 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. 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. 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. 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 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. OVERVIEW OF COLLABORATIVE NETWORKS OF ADAPTIVE SENSORS

Standard stuff from the AIST proposal and IGARSS papers

III. COGNITION AND HIGH-LEVEL COMMUNICATIONS

- What it means for low-level and high-level communications
- Cognitive communications communications
- What are high-level aspects of comm: when and where to move information given large scale constraints on the network. What are tuning parameters at this high level?
- Table of low level and high level comm issues
- Summary of different methods for dealing with this problem. Can ML help?

TABLE I. COMMUNICATION MODEL PARAMETERS

- What is ML?

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; and/or have no known "good" solution.

- How can ML be utilized in this problem: high level comm decision making and tuning

Machine learning techniques are currently being applied in the development of scheduling algorithms, sensor network design, and other applicable areas. An opportunity exists to use machine learning algorithms to optimize the flow of information within a collaborative network of satellites. Optimization will increase communications efficiency by increasing the value of data contents and reducing power consumption.

- Highlight types of ML solutions/tools that are applicable to this specific problem

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 in communications decisions.

- Identify particular tool that will be used to solve problems in the paper (i.e. classification problem solving using k-means blah blah)

This research involves the application of existing machine learning tools as well as the implementation of new machine learning algorithms. A group of third-party Python packages is used, including SkikitLearn and Tensorflow. The custom algorithms discussed are written in C++.

A. Cognitive Communications

- What is cognition
- What is cognitive communications
- Example references of how it has been applied
- Insert figure showing flow chart of problem formation and solution using the ML approach
- 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

Fig. 1. Proposed cognitive communcaitons flow chart.

IV. GENERATION OF TRAINING DATA OF COLLABORATIVE SATELLITE CONSTELLATIONS

- To train the neural network, it is necessary to generate large training datasets.
- Contents of training data should include ....

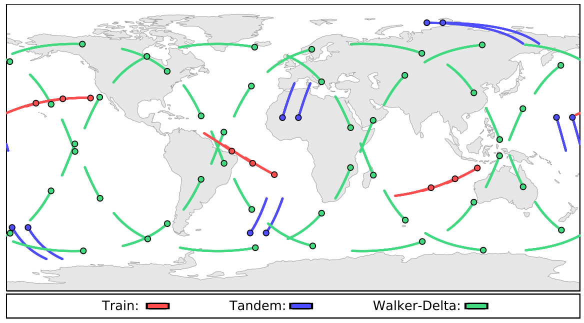
Training data should include simulation variables which are suspected of having some correlation to the parameter being optimized. These variables are expected to capture time-series data involving satellite position, health, communication hardware details, sensor hardware details, network connectivity, or other similar parameters.

- Collaborate Software Overview. collaborate

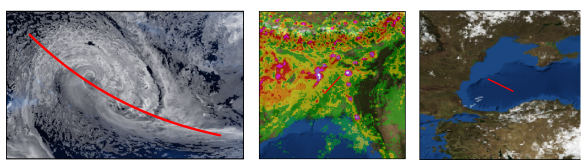
A software toolset "Collaborate" is under development which is capable of producing the described training data. The toolset has two main components: first, a C++ development library for observing system simulation experiments; and second, a Python visualization and analysis package for post-processing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

- What it simulates. What features it supports

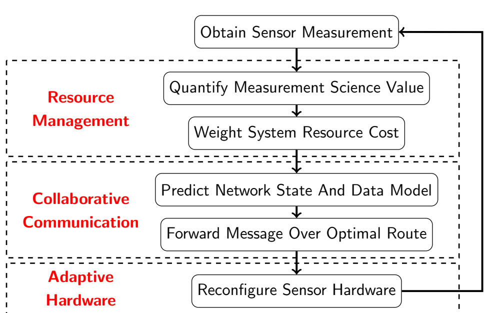
The Collaborate library offers a number of unique features valuable to future observing system simulation experiments. At its core, it is a physics engine for satellite position, velocity, and attitude. Power and RF accessories may be attached to satellites and individually oriented. The next level involves 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.

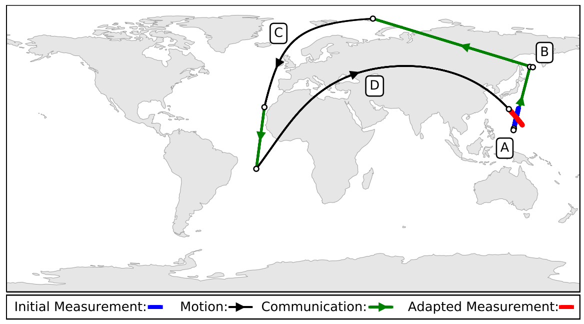


Sensor hardware is attached to satellites as an interface to truth data (NetCDF Nature Run data). This provides a custom modeling environment for real sensor hardware and enables heterogeneous sensor constellations with different capabilities. As a satellite orbits, its pointing vector intersects Earth's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



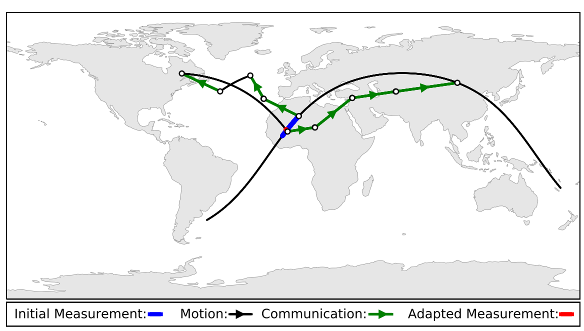
Collaborate is named for its ability to manage collaborative networks of satellites. Its implementation focuses on the high-level communication decision space previously discussed. The library employs, in addition to standard C++ components, advanced data structures including trees and graphs to execute predictive route-finding algorithms for efficient communications.

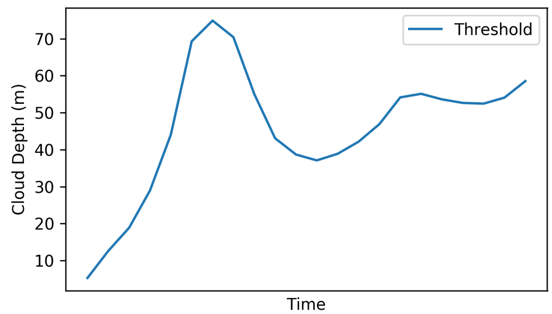




These network algorithms are the highlight of project development because they expedite two valuable capabilities for researching cognitive behavior and machine learning applications. First, Collaborate's networking algorithms provide a feedback mechanism to satellites executing deployed machine learning algorithms. Second, Collaborate produces verbose simulation data which can be used to train neural networks and other machine learning models.

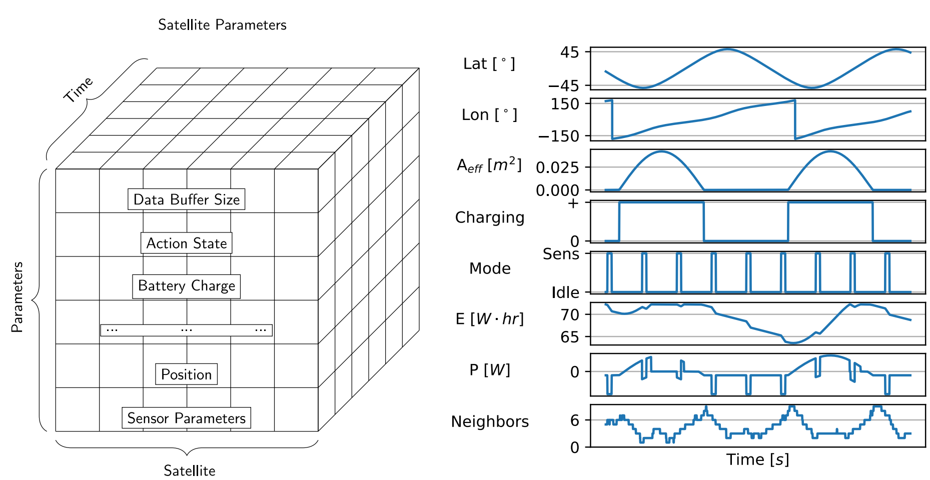
In addition to forward propogation of data, satellites can feed back relevant information to the original satellite for regression tasks. This is useful when optimizing low-level communication parameters, learning the correlation between truth data parameters, or to promote sensor hardware reconfiguration.

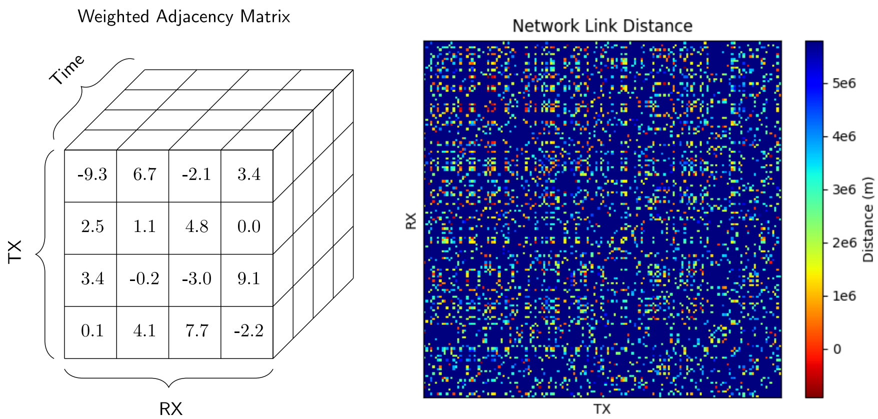




- Key is that it can output large sets of collaborative and adatpive simulation results.
- Using Collborate to generate traning data

Collaborate logs simulation data to files accessible by external machine learning tools. The provided Python packages undersand the data format and can read and store the data for later use as Numpy or Pandas data structures. Logs are provided in two main formats: first, a time series of data frames containing satellite node parameters; second, network connections are stored as adjacency matrices.





- Collaborate simulates complex algorithms that take a long time to execute to make good decisions
- Concept will be to replace these algorithms with an efficient NN.
- What was specifically generated for the case studies . . .

V. EXAMPLE CASE STUDIES

Description of examples and why they were chosen.

A. Example 1

. . .

B. Example 2

. . .

VI. SUMMARY AND NEXT STEPS

...

REFERENCES

...