Enabling Low-power Radiometers with Machine Learning Calibration

John Bradburn, Mustafa Aksoy
Department of Electrical and Computer Engineering
University at Albany, SUNY
Albany, NY, United States

Paul E. Racette, Tim McClanahan
NASA Goddard Space Flight Center
Greenbelt, MD, United States

Sheri Loftin
ADNET Systems, Inc.
Goddard Space Flight Center
Greenbelt, MD, United States

***Abstract*— Smart sensors of the future will be designed to extract maximum value information while minimizing the resources required to acquire, downlink and process data. Such intelligent instruments will reduce mission costs by avoiding taking measurements of uninteresting or unnecessary features while still capturing useful and beneficial data. However, many sensors like radiometers can make calibrated measurements only after reaching near thermal equilibrium; this requirement leads to wasted power, excess data, and delays in acquiring useful information. Furthermore, available spacecraft power and/or thermal requirements can lead to the need for power cycling a radiometer. Turning power off to an instrument stops its data acquisition but also leads to a loss of data when the instrument is powered back on until its electronics are sufficiently stable to make a calibrated measurement. As minimizing resource utilization is key to realizing future radiometer technology, in this paper, we propose the creation of a framework that uses machine learning techniques to unlock transient states of radiometers for obtaining calibrated measurements.**

I. Introduction

Reducing power draw of a radiometer can be achieved by power cycling the receiver electronics. Methods to power cycling the electronics include turning the instrument power off and powering the electronics back on once there is sufficient available power to operate or rapidly power cycling to reduce the average power draw. The latter method in addition to reducing the average power draw can be used to control the physical temperature of the electronics. The proposed framework aims to develop machine learning applications to calibrate across the radiometer transient response due to such power cycling. The outcome will be a machine learning calibration algorithm that draws upon the ability of neural networks to learn and utilize the characteristics of a radiometer's transient response and ancillary telemetry data to produce calibrated measurements with minimum uncertainty. Additionally, this approach will reduce power, data volume and turn-on time required to obtain useful information.

The proposed technology targets a broad set of calibration and data collection scenarios of radiometers. These include various external and internal calibration methods such as utilizing external blackbody and vicarious calibration references and internal-load references such as noise diodes and Dicke-switched waveguide terminations. It should be noted, this study does not address the development of calibration reference standards but rather the methods in which reference measurements are used to calibrate radiometers.

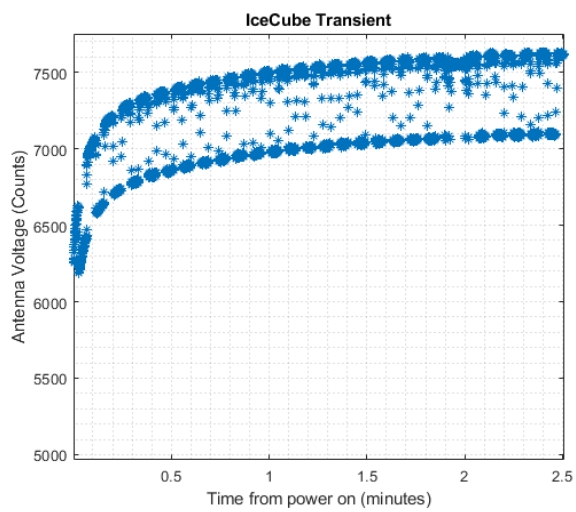

Fig. 1. IceCube pre-launch antenna voltage data demonstrates receiver transient response at instrument power-on. During flight, IceCube was power cycled every orbit due to limited spacecraft power.

II. Motivation

IceCube is a project flown by NASA Goddard Space Flight Center (GSFC) in 2017 on a 15-month mission that produced the first global maps of ice clouds using 883 GHz [1, please check]. The 3U CubeSat had roughly a 90-minute orbit period; but due to power constraints, the radiometer only operated for approximately 40 minutes per orbit. Upon turn on, the first 5 minutes of observations were removed from processing to avoid

the receiver transient response shown in Fig. 1. Then, the receiver's local oscillator was rapidly power cycled to further reduce the average power draw of the instrument.

The Submillimeter Solar Observation Lunar Volatiles Experiment (SSOLVE) is a Development of Advanced Lunar Instruments (DALI) project supported by NASA to develop a submillimeter heterodyne spectrometer for quantifying the water cycle in the tenuous lunar atmosphere [2]. The thermal environment on the moon requires SSOLVE to operate at variable duty cycle to reduce its average power and maintain its temperature within operating limits. GSFC has a Small Business Innovative Research (SBIR) Phase 3 contract with Virginia Diodes, Inc. to collect power cycle data with SSOLVE receivers to help determine the optimal power cycling sequence. Thus, calibrating the radiometer over its transient period would provide a significant improvement in science data volume.

III. Methodology and Initial results

This study entails using receiver transient response data to develop models for the complex dependence on physical temperatures and calibrated response. These models will be used to generate synthetic radiometer data for training and testing the performance of a machine learning algorithm. Using synthetic data has the advantage of studying the performance and limitations of machine learning algorithms without concern of systematic errors inherent in actual measurements. A generalized framework will be developed that allows for the decimation of data into frames suitable for a machine learning algorithm. This algorithm will leverage mutual information in calibration measurements, as well as integrated telemetry data (such as payload temperature measurements, age of instrument, and position) [3], and modeled uncertainties [4, 5]. Measurement uncertainty will be used as a figure of merit to compare the performance of the machine learning algorithm with conventional least-squares-regression based calibration algorithms [6]. Finally, the algorithm will be tested using laboratory/thermal vacuum data from one or more radiometer systems. While the transient models will be developed using specific receiver types, the framework for implementing, training, and validating the machine learning algorithm will be more broadly applicable.

In an initial study on machine learning calibration, radiometer data were synthesized with a variety of systematic and random fluctuations. These data were used to train a convolutional neural network (CNN) to produce estimates of calibrated brightness temperature measurements. Over a broad range of conditions, the CNN was shown to outperform traditional least-mean-square (LMS) regression techniques as shown in Fig. 2. Other studies into radiometer calibration with neural networks see promising results as well [7]. Thus, the proposed technology serves to benefit future missions with similar types of power constraints, whether they may only need to operate for a short period of time like SSOLVE, or need to maintain low average power over a long period of time.

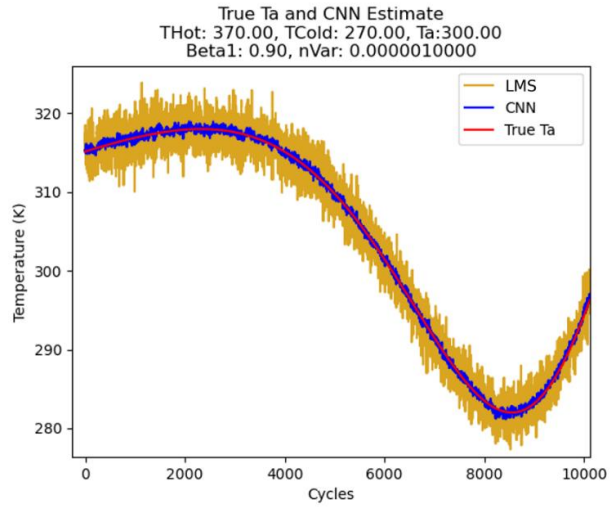

Fig. 2. Calibration of synthetic radiometer data using a convolutional neural network (blue) and least-mean-square regression calibration methods (yellow). The CNN utilizes transient information not used by conventional regression methods to yield lower measurement uncertainty. These initial simulations show great promise for machine learning to calibrate a radiometer across its transient response.

Acknowledgement

This work was supported by a NASA Space Technology Graduate Research Opportunity.

References

[1] Dong L. Wu, Jeffrey R. Piepmeier, Jaime Esper, Negar Ehsan, Paul E. Racette, Thomas E. Johnson, Brian S. Abresch, Eric Bryerton, "IceCube: spaceflight demonstration of 883-GHz cloud radiometer for future science," Proc. SPIE 11131, CubeSats and SmallSats for Remote Sensing III, 1113103 (30 August 2019); https://doi.org/10.1117/12.2530589

[2] Livengood et al. LPSC 2019, Submillimeter Solar Observation Lunar Volatiles Experiment (SSOLVE) https://www.hou.usra.edu/meetings/lpsc2019/eposter/1640.pdf

[3] M. Aksoy, H. Rajabi, P. E. Racette and J. W. Bradburn, "Analysis of Nonstationary Radiometer Gain Using Ensemble Detection," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 13, pp. 2807-2818, 2020, doi: 10.1109/JSTARS.2020.2993765.

[4] M. Aksoy, P. E. Racette and J. W. Bradburn, "Analysis of Non-Stationary Radiometer Gain Via Ensemble Detection," IGARSS 2019 - 2019 IEEE International Geoscience and Remote Sensing Symposium, Yokohama , Japan, 2019, pp. 8893-8896.

[5] J. Bradburn, M. Aksoy, and H. Ashley, "ACCURACy: Adaptive Calibration of CUbesat RAdiometer Constellations," USNC-URSI National Radio Science Meeting 2021, Virtual Meeting, (Submitted Sept 2020)

[6] P. Racette and R. H. Lang, "Radiometer design analysis based upon measurement uncertainty," Radio Science, vol. 40, no. 05, pp. 1-22, Oct. 2005.

[7] M. Ogut, X. Bosch-Lluis and S. C. Reising, "A Deep Learning Approach for Microwave and Millimeter-Wave Radiometer Calibration," IEEE Transactions on Geoscience and Remote Sensing, vol. 57, no. 8, pp. 5344-5355, Aug. 2019.