Reducing Instrument Power Using Machine Learning Calibration

John Bradburn[(1)], Mustafa Aksoy[(1)], and Paul E. Racette[(2)]
(1) University at Albany SUNY, Albany, NY, USA; e-mail: jbradburn@albany.edu; maksoy@albany.edu
(2) NASA Goddard Space Flight Center, Greenbelt, MD, USA; e-mail: paul.e.racette@nasa.gov

Future space-borne sensors will be able to extract the maximum information content from data products, while minimizing the resources required to acquire, downlink, and process data. In-orbit radiometer measurement calibration is required to correct for receiver fluctuations, but well-calibrated measurements typically require instrument equilibrium. Instrument power cycling can be used to maintain equilibrium and manage instrument power use but leads to pauses in data collection when the instrument is powered off. Rapid power cycling can reduce the period of data gaps, but results in increased measurement uncertainty due to induced transients in the receiver response. A convolutional neural network (CNN) model has been shown to improve the root-mean-square error (RMSE) in calibrated measurements using synthetic radiometer data (Fig. 1).

Data collected from laboratory receivers have been analyzed to learn the receiver gain characteristics and properties of the transient effects at the receiver turn on. These data are used for tuning a synthetic radiometer model [1, 2] that is used to generate a training dataset for the CNN. The CNN model is evaluated on laboratory data collected within this training distribution. The result is a CNN trained on a dataset bootstrapped from real laboratory measurements and used to obtain calibrated measurements from a second independent laboratory dataset. The analysis of the laboratory data will be presented along side the results of the CNN calibration on data collected from a real system under laboratory conditions. The transient effect at receiver turn-on present in these laboratory data and the implications of a transient model to reduce instrument power in conjunction with a CNN calibrator will also be discussed.

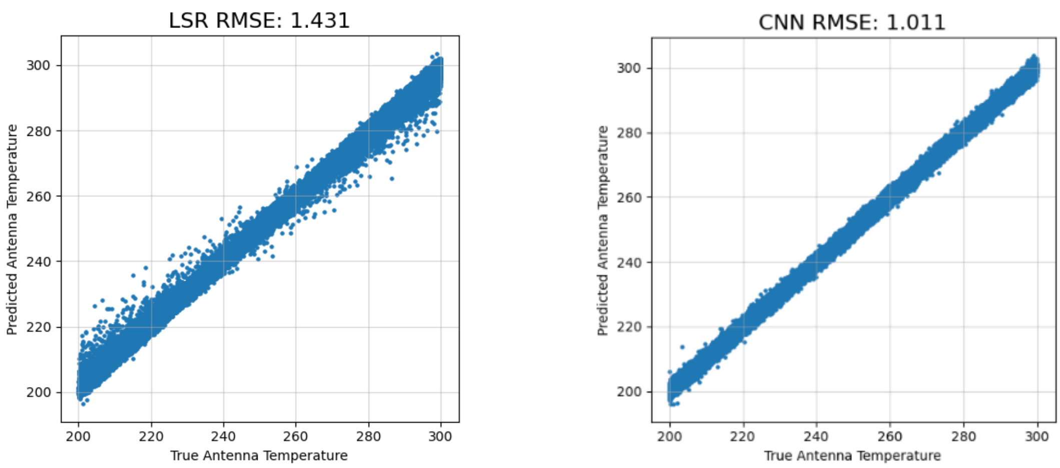

Figure 1. (Left) RMSE of 128k simulated radiometer data samples using a linear-least-squares estimator, (Right), RMSE of the same data set using a CNN trained to predict antenna scene brightness temperatures from a dataset of two calibration references.

References

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