A Deep Learning Approach to Detection and Mitigation of RFI in Radiometric Measurements

R2 – Reconfigurable Digital Signal Processing Systems

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Abstract

Water vapor is a greenhouse effect gas vital for atmospheric predictions. We use microwave radiometers to obtain water vapor profiles from the atmosphere by calculating brightness temperature, which reflects the energy absorption at specific frequencies, especially between the 22-30 GHz (K-band) range where the absorption rate of water vapor is higher. We propose advances on using autoencoders interferences in order to obtain clean water vapor profiles. The methodology involves an experiment on four different architectures (Convolutional, Sparse, LStM and Variational) to test performance and choose the best one. An experiment was designed to measure the impact of interference on water vapor profiles.

Problem and Hypothesis

The problem addressed in this proposal is how to determine the performance of denoising autoencoder architectures for Radio atmospheric radiometric measurements on K-band frequency. Different methods have been used to address the various types of RFI [1]. Statistical analyses have been used to detect sporadic RFI [2], while specialized algorithms in the polarimetric and frequency domains have been used to tackle continuous RFI. However, RFI sources are expected to grow for the water vapor observation bands due to the increasing congestion of radio signals[3] and regulatory constraints related to FCC-licensed bands as shown in Table 1. Current methods and techniques not always are able to detect domain-specific interferences due to the limitations of their scope.

Lease ID in FCC	Lower bound (GHz)	Upper bound (GHz)	Collides with radiometer channel? (Yes/No)
WRES540	24.25	24.35	No
WRES823	24.35	24.45	No
WRET265	24.75	24.85	No
WRET534	24.85	24.95	No
WREU655	24.95	25.05	Yes
WREU940	25.05	25.15	No
WREV411	25.15	25.25	No
WRBC252	27.925	28.35	Yes
WPOJ996	29.1	29.25	No
WPOJ996	31.075	31.225	No

Table 1: Licensed frequency ranges in Mayag¨uez for K bands

We have identified RFI at 28 GHz in radiometric measurements captured locally by comparing them with the expected water vapor absorption behavior over the observation frequency range, illustrated on Figure 1.

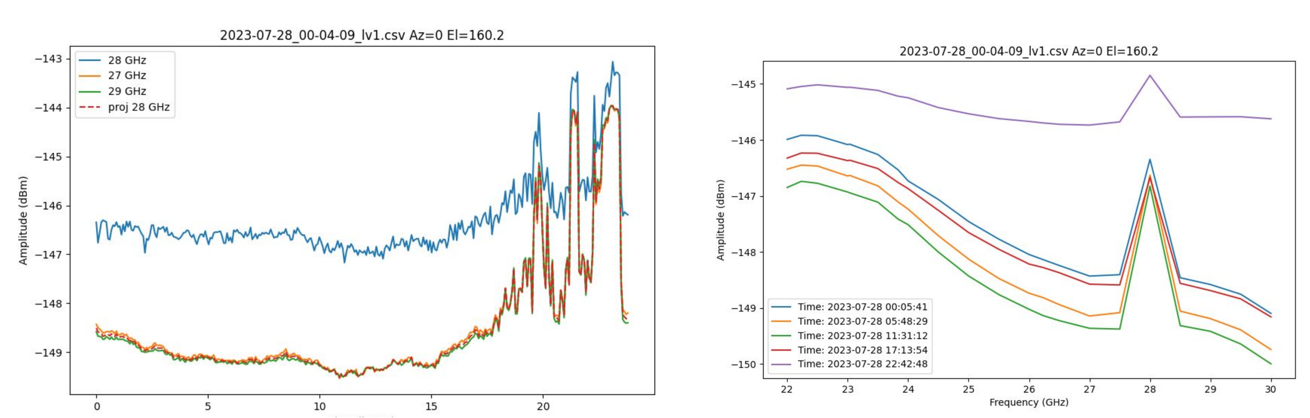

Figure 1: RFI found at 28 GHz in K-band

Why Deep Learning?

Previous studies have shown that deep learning models can surpass classical methods concerning signal-to-noise (SNR) ratio and area-under-curve for Receiver-operating-characteristic (AUC) in similar RFI approaches. Deep learning have advantages over traditional methods because of: data-driven approach, adaptability and automation [4]. Previous work published by Ristea et al [5] and Sun et al [6] showed significant improvement with respect to SNR (144.78%), AUC (2.1%) and precision (9.3%).

Objectives

The main objectives of this research include:

- Studying the impact of different types of RFI on the water vapor measurements obtained with a microwave radiometer
- Exploring the use of deep learning models to detect and mitigate different types of RFI in the operation of microwave radiometers.

Methodology

Autoencoders are models in deep learning that map input data to an internal representation called the latent space, produce output similar to the input data by applying transformations and filtering techniques, explained in figure 2[8]. The proposed methodology includes the comparison of four different autoencoder architectures (Convolutional, Long-Short Term Memory, Sparse and Variational) illustrated in figure 3.

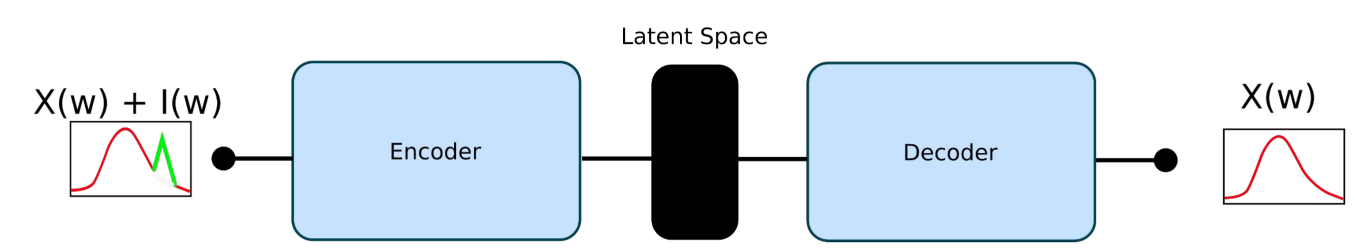

Figure 2: Basic autoencoder architecture

The training process will include a synthetic signal and noise generator. The noise generator will be based on central frequency, noise intensity and continuum propagation to simulate real conditions. The signal will be constructed using the water vapor absorption model proposed by Cruz-Pol et al [9] with variations on Center absorption frequency strength, continuum absorption strength and curve width. These variations have the purpose of simulating the current radiometer calculations of Brightness temperature and will be the foundations of the training dataset

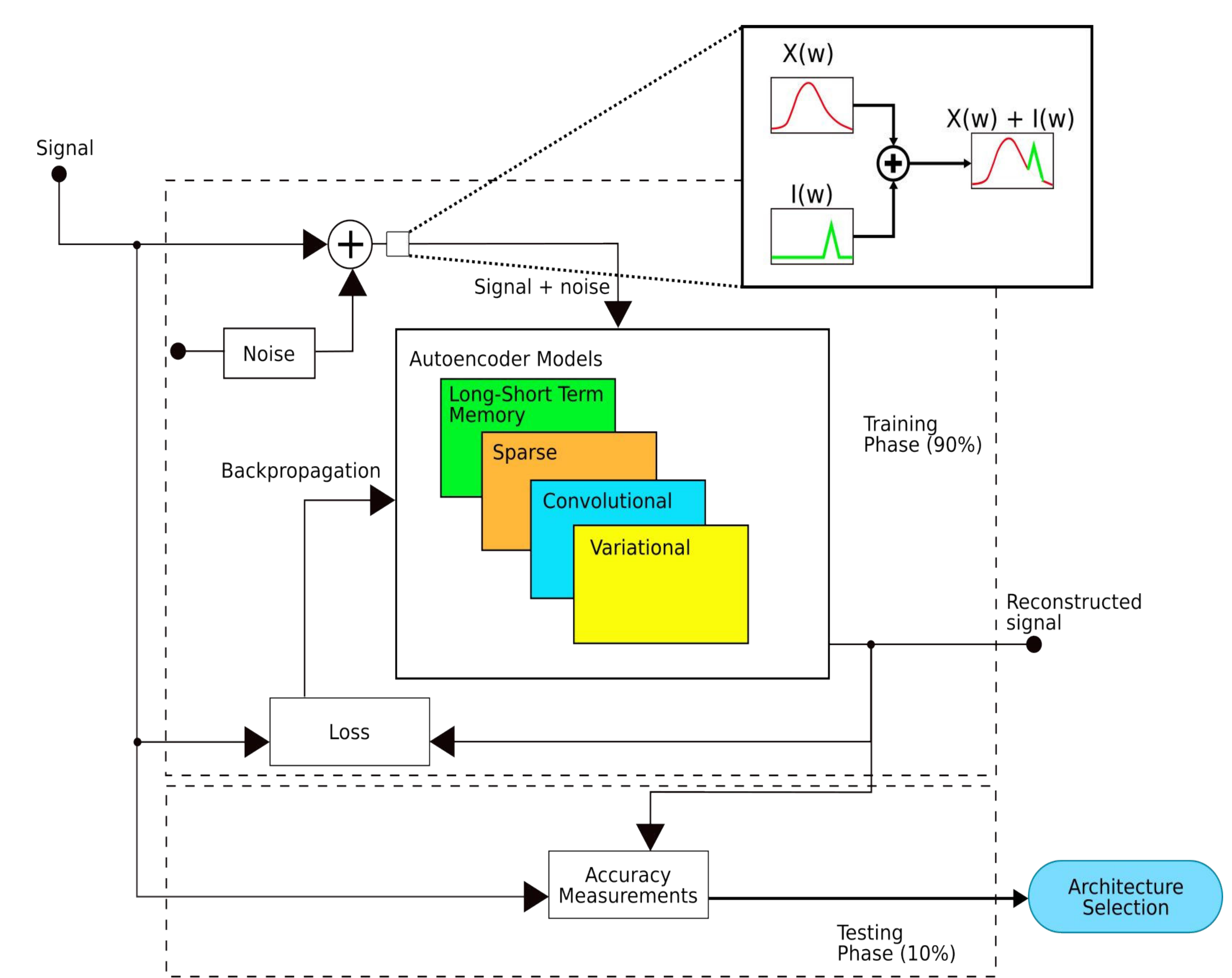

Figure 3: Model Training Architecture

We will use the R&S SMW200A signal generator to inject and adjust the intensity, center frequency, duty cycle, and modulation to determine which ones most significantly influence the accuracy of the radiometer, illustrated on figure 4. This parameters will define a full-factorial experiment design.

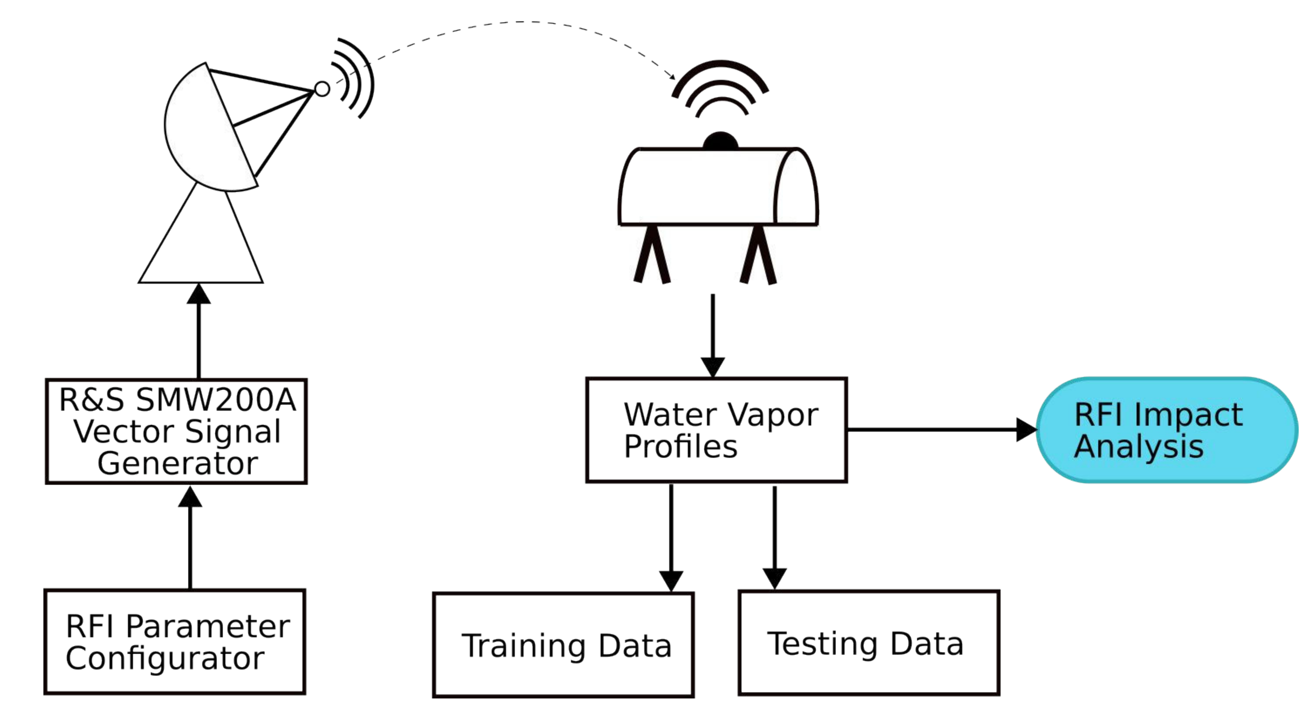

Figure 4: Experimental Design for RFI injection

Expected Results

- A Better understanding of the effect of RFI on radiometer data in K-band measurements for water vapor profiles.
- A Detailed knowledge of the effectiveness of autoencoders and neural networks in RFI detection and mitigation.
- A working model for RFI mitigation in K-band data deployed on the radiometer computer to actively remove interference.

Future Work

- Studying the interference impact on water vapor profiles based on an experiment injecting different types of RFI.
- Implementing the autoencoder architectures and train with synthetic noise added to rfi-free radiometer readings.

References

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