SSC23-S2-05

Machine Learning Radio-Frequency-Based Anomaly Detection for Ground Station and Satellite Telecommunication

"Raffaele Bua", "Lucia Necchi", "Pietro Corrado", "Matteo Cappella", "Bérenger Villat", "Giovanni Pandolfi"
"Leaf Space"
"Via Cavour, 2, 22074 Lomazzo CO" ; "+39 02 3671 4624"
Raffaele.bua@leaf.space

ABSTRACT

Satellite-to-ground station telecommunication is a crucial aspect of satellite missions, representing a single point of failure of the entire space system.

Each failed contact is an issue for all satellite missions, leading to a potential data loss. The detection and forecasting of data transfer failures are critical challenges in satellite operations, given the unpredictability and variety of potential causes for such anomalies.

Considering the spectral waterfall plot the most appropriate tool to describe the anatomy of satellite contacts, an automatic waterfall analysis could help satellite mission operators, by promptly discovering potential data transmission failures between satellites and ground stations, and by forecasting anomaly behaviors.

The work reported in this paper exploits machine-learning models, trained with spectrogram waterfall diagrams to provide real-time and automatic anomaly detection of data transmission failures. Long-Short Term Memory and Deep learning models have been trained and validated, for anomaly detection and forecasting of contacts failures, with a dataset encompassing a semester's worth of satellite contacts in both S-band and X-band.

With examples to identify the most appropriate model, this research will present practical outcomes and data-informed best practices in support of mission operators.

INTRODUCTION

RF (Radio Frequency) communications in satellite systems are susceptible to various anomalies that can degrade the quality of the signal, disrupt communication, or even lead to complete signal loss. In recent years, there has been a growing interest in developing effective anomaly detection techniques to address these challenges and improve the overall performance and reliability of satellite communication systems.

Anomaly detection in RF communications involves the identification and characterization of abnormal events or patterns that deviate significantly from the expected behavior. In the context of satellite communications, anomalies can arise from a multitude of sources, including environmental conditions, and equipment malfunctions. Valuable insights into the spectral characteristics and temporal dynamics of the RF signal are obtained through the signal waterfall plot.

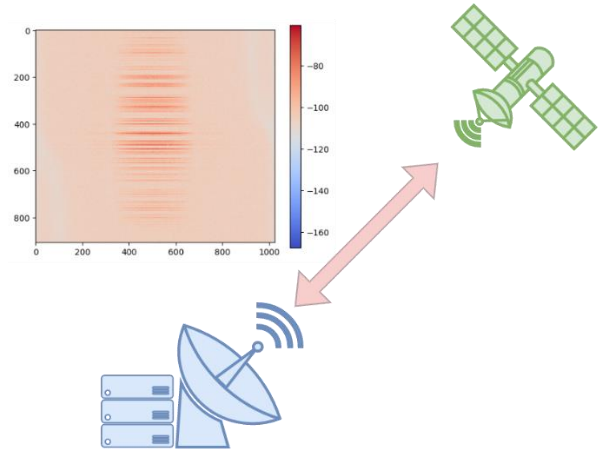

Figure 1: Telecommunication between a ground station and a satellite.

Traditional approaches for anomaly detection in RF communications rely on manually designed threshold-based methods or rule-based systems that compared the observed signal characteristics to pre-defined thresholds.

In our research, we present an approach to anomaly detection which uses machine learning techniques. We explore the effectiveness of LSTM recurrent neural networks in forecasting the RF waterfall, and in detecting anomalies by comparing predicted RF waterfall with real behavior. By establishing a maximum deviation threshold, we could identify instances where the signal diverges significantly from the predicted forecast, indicating the presence of anomalies. This methodology serves as a simple yet powerful application for anomaly detection, highlighting the potential of LSTM networks in this domain.

DATASET

The data used for this research encompasses six months of waterfall RF data for S-band and X-band communications, providing a comprehensive and representative set of samples for the model selection and assessment processes. The dataset counts about 500 RF waterfall samples. A distinct contact between a satellite and a ground station is represented by each sample, portraying a waterfall RF signal.

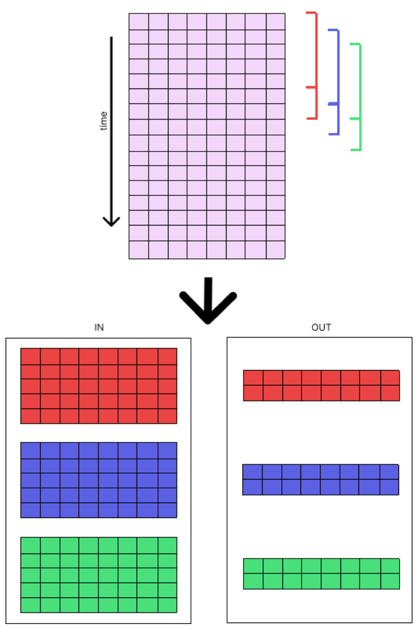

Figure 2: Dataset processing with sliding windows.

In this study, the dataset utilized was obtained from the Leaf Space ground station network. To ensure the incorporation of a wide spectrum of environmental conditions, satellite operations, and communication scenarios, the data collection procedure involved the continuous capture of waterfall RF signals over a duration of six months.

To facilitate the training of the LSTM model, the waterfall RF data is preprocessed and organized into input-output pairs. The input data consists of a sliding window of n time-stamps on which predictions are made, capturing the temporal dependencies in the RF spectrum. The output data are the corresponding m time-stamps in the future, representing the desired prediction. This ensures the LSTM model learns to forecast the future behavior of the RF signal based on past observations.

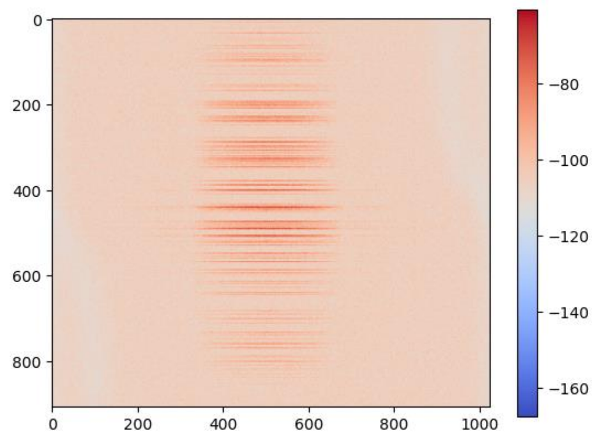

Figure 3: Waterfall of an S-band signal sample.

The model was trained and assessed using the hold-out technique: the dataset was divided into two main subsets used in the respective phases. It was chosen not to perform k-folding as the chunk extraction process explained above contributed to a significant increase of the actual data-points fed to the model. The initial subset, which constituted 90% of the samples, was utilized for the model selection stage. The remaining 10% of the dataset was reserved for the model evaluation phase. To adequately tackle concerns related to underfitting and overfitting, the model selection subset was subsequently split into two separate datasets: one for training the model and another for validation purposes.

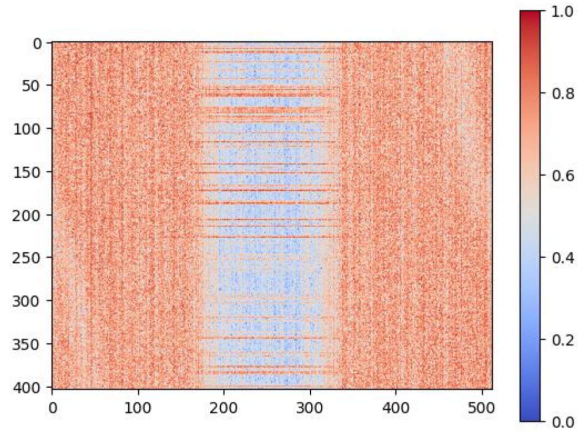

Figure 4: Normalized and reduced S-band waterfall plot sample.

The data underwent preprocessing prior to being used in the experiments. All waterfalls plot were subjected to normalization, resulting in values ranging from 0 to 1. This standardization technique is widely acknowledged to enhance performance in machine learning tasks.

METHOD

Currently, there are two main approaches to anomaly detection. The traditional approach involves setting thresholds that determine the limits outside of which a data point will be considered anomalous. Although this approach has the advantage of being very cheap under a computational point of view, it has the limitation of requiring ad-hoc knowledge and experience to determine the thresholds (Langfu CUI, 2021). For this reason, traditional methods lack scalability and present quite a significant overhead per scenario, particularly since satellite communications are not strictly standardized and as such present a vast range of scenarios. Therefore new data-driven approaches are favorable in this context. Their usage has been well documented in a multitude of usages, such as fraud detection (Waleed Hilal, 2022) and manufacturing monitoring (Andrey Kharitonova, 2022). However, some of these approaches, such as k-NN classification do not extend well to scenarios where data also has a temporal dimension (M. Munir, 2019), while other approaches, such as Support Vector Machines, required label data to be trained, which implies significant limitations in terms of accessibility and scalability of the model.

Studies such as (Nistha Tandiya, 2018) provide encouraging proof that such methods can also be successfully applied to spectrum activity analysis, so the data in the form of a time series. However, most existing work concerns wireless networks as the diffusion of technologies such as IoT has put increasing importance on being able to detect potential security threats in real-time.

In this paper, we look at extending this approach to satellite communications which present some additional difficulties. Unlike Wi-Fi, which operates on standardized protocols, satellite communications lack such standardization, making the detection of anomalies more challenging. Furthermore, satellite communications are inherently less reliable due to factors such as atmospheric conditions, signal interference, and signal degradation over long distances. This kind of spectrum activity also has an added layer of complexity due to the measures in place to compensate for the Doppler effect.

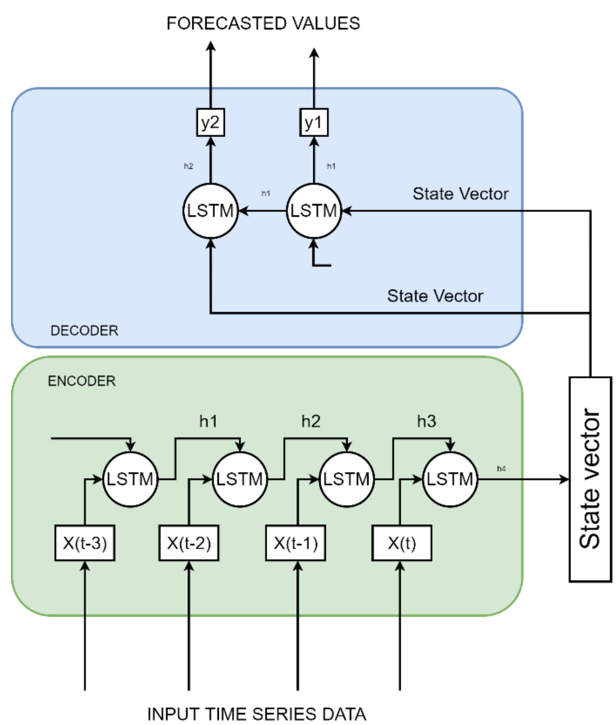

Figure 5: Architecture of sequence-to-sequence LSTM with encoder and decoder layer.

Advancements in artificial intelligence (AI) and deep learning is revolutionizing various domains, including space telecommunications and anomaly detection approaches. Considering the temporal nature of RNNs models, we conducted experiments utilizing an LSTM (Long Short-Term Memory) sequence-to-sequence with encoder and decoder layer model that was specifically tailored for the purpose of forecasting the RF waterfall in satellite ground station communications, particularly in the S-band and X-band frequencies. The primary objective of this model is to predict the future behavior of the signal Fourier transform in order to then detect anomalies by comparing the observed waterfall with the forecasted waterfall.

The proposed LSTM sequence-to-sequence model comprises two primary layers: an encoder and a decoder layer. The encoder layer accepts the historical sequence of signal Fourier transform as input and acquires the ability to extract pertinent characteristics from the data.

The decoder component then utilizes the encoded features to generate the forecasted signal waterfall for future time steps. The architecture of the LSTM sequence-to-sequence model is illustrated in Figure 5.

Given the task of forecasting the signal waterfall, the mean squared error (MSE) loss has been used, to measure the discrepancy between the predicted and the real signal. During the training phase, the model optimizes the parameters by minimizing the MSE loss using gradient descent-based optimization Adam algorithm.

Once the LSTM sequence-to-sequence model is trained, it can be utilized for anomaly detection by comparing the observed signal waterfall with the forecasted plot. Anomalies are detected when there is a significant deviation between the two plots. To quantify the dissimilarity between the observed and forecasted signals, we used the mean squared error.

By setting the appropriate threshold, data behavior can be classified as anomalous. The LSTM model, combined with an anomaly detection mechanism, could provide a framework for real-time monitoring of signal waterfalls and the timely identification of anomalies.

During our experiments, we performed a model selection exploiting a grid search, with the goal of optimize the hyperparameters of the best model. We considered MSE as a performance parameter to select the model, being a regression task. Then we performed the model assessment, extracting the performances using a portion of the dataset, not used during the model selection phase.

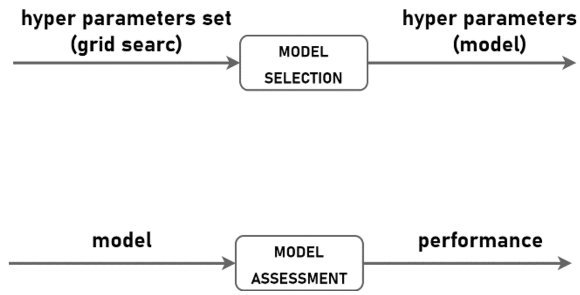

Figure 6: Model selection and model assessment processes.

During the model selection phase, we trained and evaluated several different hyperparameter sets using hold-out cross-validation. The models were assessed based on their performance on the testing set, and the model with the highest performance was selected as the final model.

RESULTS

During the model selection phase, some hyperparameters were taken into account. These included the number of LSTM units, the number of past time steps, the number of future time steps, and the training epochs. The LSTM units parameter determines the number of memory cells within the LSTM layer. The number of past time steps hyperparameter defines the size of the window on which the prediction is made. The number of future time steps hyperparameter indicates the number of forecasted waterfall diagram rows in the model's future predictions.

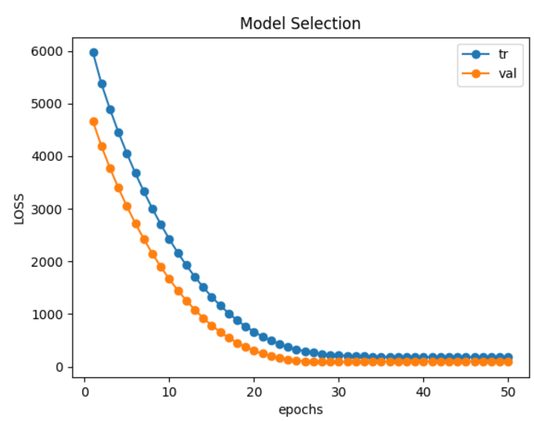

Figure 7: Loss chart of selected best model, during the training phase, for S-band signal.

For each model selection phase execution, we have obtained the train and validation error chart, during the epochs. The Figure 7 shows the loss plot, generated during the best model training.

After careful experimentation and evaluation, the best model configuration was identified. The hyperparameters identified are shown in the Table 1

Table 1: Best model hyperparameters.

Hyperparameter	Value
LSTM Units	10
Number of the past time steps (as input)	5
Number of the future time steps (forecast)	1
Training epochs	50

The top-performing model achieved a mean squared error of ~183 in the assessment phase, when comparing the actual and predicted RF waterflows.

We have generated a plot of the forecasted waterfall, using the selected model (Figure 8).

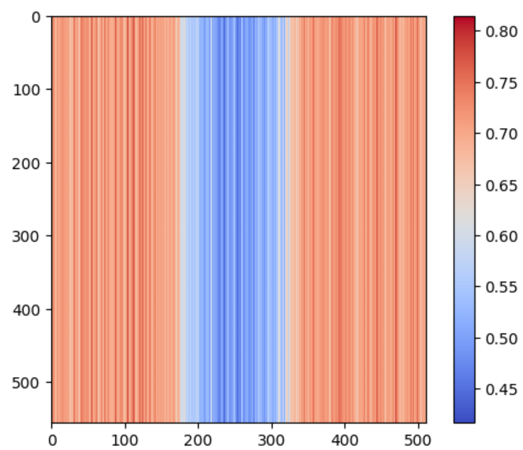

Figure 8: Forecasted waterfall by the best LSTM model for S-band signals.

As show in the Figure 8, the model identifies the common pattern of RF waterfall, with the most recurrent frequencies occupied by the signal. The behavior on the y axis is not picked up well due to the fact that generally the patterns along the time axis are not as strong and mainly depend on what kind of packets are exchanged, which is related to the specific data that is being transmitted, and not on absolute patterns.

Other models could perform better for the anomaly detection, like convolutional deep neural networks using labeled datasets. The main focus of this study is to understand the adequacy of sequence-to-sequence LSTM in the field of waterfall analysis; being the LSTM and in general the RNNs models used with time series. The architecture of these models is clean and the theory behind is well structured. However, in our case and our implementation, this model could be a simple solution for early anomaly detection analysis. Targeting an advanced anomaly detection system for waterfall, we could suggest to the reader that pattern recognition models for images could extract more features from this kind of data; however, taking into consideration that RNNs models lends themself well to incremental and real-time data.

ANOMALY DETECTION WITH LSTM

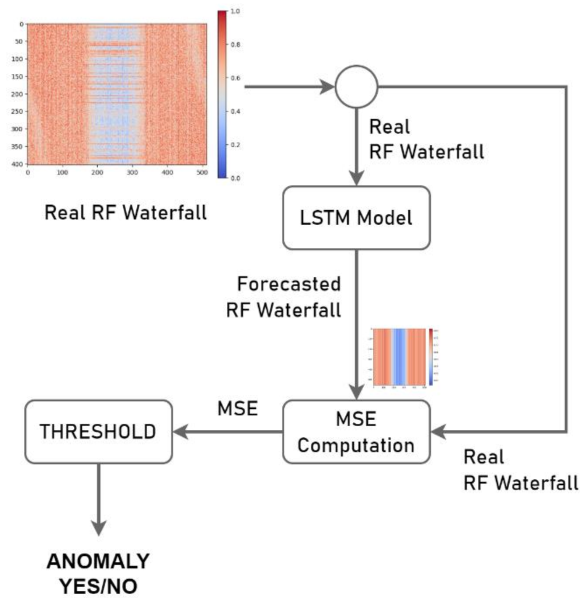

Figure 9: Anomaly detection system architecture, with LSTM models.

Figure 9 shows the design of a system that detects anomalies in RF waterfall of S-band and X-band signals, based on LSTM models. The input of this system is the RF waterfall obtained from the radio, step by step in real-time. The real waterfall becomes the input of the LSTM model that forecasts the future rows of the plot. The system computes the MSE of the real and the forecasted waterfall time-step by time-step. If the error exceeds the threshold, the system identifies a potential anomaly alarm, inviting a human operator to check the contact between the satellite and the ground station.

FUTURE WORKS

Considering the results obtained with sequence-to-sequence LSTM model experimented in this work, future research involves exploring pattern recognition models applied to the RF waterfalls as images. These models can help identifying distinct patterns or clusters within the RF waterfalls data, that could be associated with different types of anomalies. This includes a supervised approach of the machine learning, producing a proper labeled dataset with a large collection of nominal and abnormal different cases.

CONCLUSION

In conclusion, our research has demonstrated that LSTM (Long Short-Term Memory) models exhibit a good performance in forecasting of RF waterfalls, which could potentially be exploited to detect anomalies in the signal. This model possesses the capability to capture frequent patterns in Fourier transform time-series of the RF signal received from the satellite in S-band and X-band. The study was motivated by the theoretical elegance of Recurrent Neural Networks; however, the obtained performances and results indicate the need to investigate alternative Machine Learning models for addressing anomaly detection in Satellite-ground stations RF communications. To focus on implementing a sophisticated anomaly detection system for waterfall analysis, we will consider the use of pattern recognition models, specifically designed for images, considering waterfalls plots as images instead of time-series data. These models have the potential to extract a greater range of features from this type of data.

References

1. Andrey Kharitonova, A. N. (2022). Comparative analysis of machine learning models for anomaly. Procedia Computer Science.
2. Langfu CUI, Q. Z. (2021). A method for satellite time series anomaly detection. Chinese Journal of Aeronautics..
3. M. Munir, S. A. (2019). DeepAnT: A Deep Learning Approach for Unsupervised Anomaly Detection in Time Series. IEEE Access.
4. Nistha Tandiya, A. J. (2018). Deep Predictive Coding Neural Network for RF Anomaly Detection . Communications Workshop.
5. Pankaj Malhotra, L. V. (2015). Long Short Term Memory Networks for. European Symposium on Artificial Neural Networks.
6. Waleed Hilal, S. A. (2022). Financial Fraud: A Review of Anomaly Detection Techniques and. Expert Systems with Applications
7. Ian Goodfellow, Yoshua Bengio, Aaron Courville (2016). Deep Learning. MIT Press
8. Trevor Hastie, Robert Tibshirani, Jerome Friedman. (2009). The Elements of Statistical Learning. The Springer