State Predictor of Classification Cognitive Engine Applied to Channel Fading

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Abstract*—This study presents the application of machine learning (ML) to a space-to-ground communication link, showing how ML can be used to detect the presence of detrimental channel fading. Using this channel state information, the communication link can be used more efficiently by reducing the amount of lost data during fading. The motivation for this work is based on channel fading observed during on-orbit operations with NASA's Space Communication and Navigation (SCaN) testbed on the International Space Station (ISS). This paper presents the process to extract a target concept (fading and not-fading) from the raw data. The pre-processing and data exploration effort is explained in detail, with a list of assumptions made for parsing and labelling the dataset. The model selection process is explained, specifically emphasizing the benefits of using an ensemble of algorithms with majority voting for binary classification of the channel state. Experimental results are shown, highlighting how an end-to-end communication system can utilize knowledge of the channel fading status to identity fading and take appropriate action. With a laboratory testbed to emulate channel fading, the overall performance is compared to standard adaptive methods without fading knowledge, such as adaptive coding and modulation.

***Keywords*—fading, machine learning, mitigation, kernel methods, supervised learning**

I. Introduction

Channel fading is a phenomenon that occurs when radio waves are blocked or reflected by physical objects that are reflective to radio frequency (RF) waves in the frequency of transmission. Fading is characterized by rapid movement of the power per unit time, which can cause data loss in the receiver. Methods such as adaptive coding and modulation (ACM) allow some channel fading to be mitigated by dynamically adjusting the link parameters. However, during deep fades or shadowing effects from physical obstructions, data loss can still occur even with adaptive methods.

The motivation for this work was based on testing with an experimental communications payload onboard the International Space Station (ISS), denoted the Space Communications and Navigation (SCaN) Testbed. This payload is used to conduct communication experiments using re-programmable software defined radios (SDRs). Due to the configuration of the antenna onboard the SCaN Testbed, its position relative to ISS and pointing angle to the GRC ground station, it has been observed that this link experiences channel fading. The severity of the fading varied significantly, depending on the geometry of the event. On the ISS, there are several sources of fading, including physical blockages from neighboring payloads and multipath from the complex structure [1].

Currently, there are no channel fade mitigation methods implemented on SCaN Testbed to address this problem. The operational procedure is for the transmitter to continue sending data throughout the fade in the hopes that some data can be decoded. In [2], a threshold-based ACM controller was applied and shown to be effective in tracking most of the channel fades. However, depending on the channel latency, severe multipath and shadow fading conditions still disrupted the link, even with the adaptive feedback loop. If the system had knowledge of its expected channel state it could modify link parameters accordingly, to reduce margin in clear sky conditions or increase system margin during fading conditions or transmit idle data until a momentary obstruction passes.

Current approaches for handling detrimental channel fading from obstructions are based on creating models over time based on human experience [3]. A complex structure like the ISS is continually evolving and changing as modules and experiments are added or removed. This provides additional motivation for developing an automated approach for detecting the presence of fading or obstructions. By classifying the difference in states and predicting whether a signal will be in fading (high fading) or not, a link could transfer data more efficiently without loss of data or re-transmission.

This paper presents the State Predictor of Classification (SPoC) Cognitive Engine (CE) as an alternative method for managing space links that have high fading profiles by detecting the presence of these fading characteristics and performing appropriate actions to mitigate their effects on mission objectives. Such an algorithm can be used alongside standard adaptive methods like ACM to provide robust communications in dynamic environments.

The paper is organized as follows. Section II presents the methods for developing the SPoC CE algorithm and the verification steps taken to evaluate the model. In Section III, a laboratory testbench, used to validate SPoC is presented and results from that study are shown comparing performance with respect to other adaptive algorithms. A discussion of the results follows in Section IV. Finally, conclusions and next steps are contained in Section V.

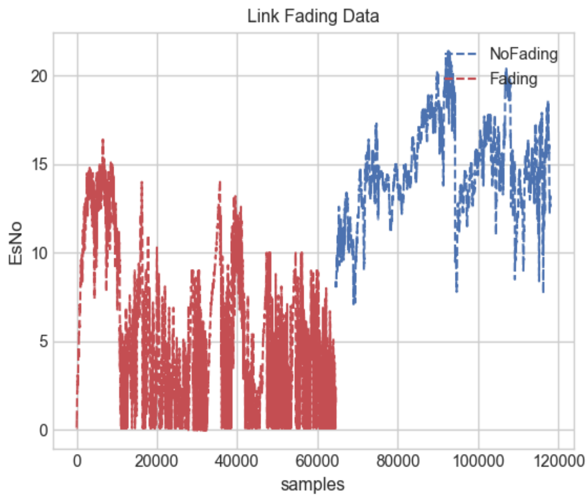

Fig. 1. Link fading data after concatenation of selected events and labeling

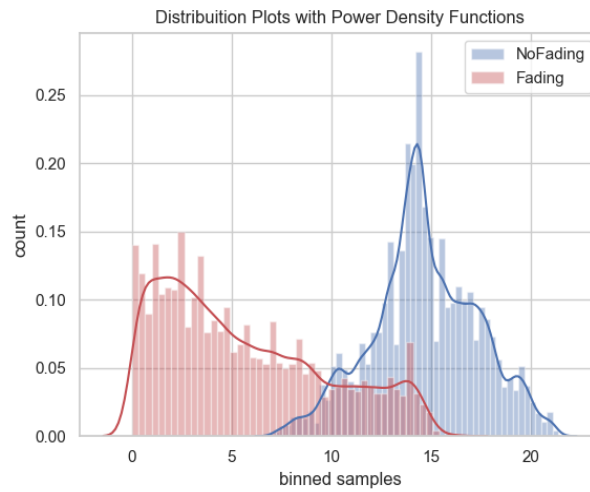

Fig. 2. Distribution plots with power density functions of the labeled data

II. Methods

A. Data Pre-Processing

A number of events have been recorded from direct-to-Earth communication events between the SCaN Testbed on ISS and the GRC ground station. Link metrics are routinely captured at the ground station including the modem's estimated Es/No (energy per symbol to power spectral density) versus time, at a rate of 100 Hz. These measurements are a way of representing the energy profile as seen by the receiver of the communication events between the ground station and the SDR on ISS.

A number of these profiles were collected and concatenated to form a database of profiles. Then the periods of high fading and low fading were labeled by visual inspection and prior knowledge of where the signal was lost and where the system was able to capture data. Often this detrimental fading corresponds to physical blockage from neighboring payloads on the ISS external structure or solar panel obstructions [1][2]. A total of 11 profiles were used originally but this number was reduced to 8 because of duplication in the effect seen by the link. The extra data was not presenting new information that would help the model select a specific state.

This process yielded a total number of 117935 Es /No values labelled as "Fading" or "NoFading". This data is plotted in Fig 1. Note that the physical phenomenon of RF fading has a small component in the signal represented in the dataset with label "NoFading". This nomenclature was chosen to distinguish between classes, not to describe the actual presence of such phenomena, in all its magnitudes, inside the signal. The target is to detect high fading regions with the following characteristics:

- Rapid fluctuation of the amplitudes or high oscillation,
- Signal that has been received but is otherwise unable to be decoded due to high noise floor or other issues.

B. Data Exploration

After the initial data pre-processing was completed, data exploration was performed to determine the best approach for creating a model capable of defining the target class in situ. A distribution plot of the two subsets was created to understand their characteristic similarities or differences, and additional descriptive statistics were run to see these characteristics visually. Fig 2 shows the distributions of the two subsets. This process revealed that the "Fading" data has an f-distribution of high variance while the "NoFading" data has a normal distribution with a large peak. Therefore, constructing a model that can detect high variance or long tails in a distribution would be preferable for the purposes of this research.

From this data exploration process it was concluded that binary classification would be possible as an initial method for determining the presence of fading on a link with similar characteristics to the presented dataset. It was concluded that features which characterize distribution peak, distribution spread, and the presence of long tails would be preferable to make a proper classification. Although mean and standard deviation would be a good starting point, these two features alone may not be able to describe the presence of the random fluctuations observed in the fading state. Additionally, the fading distribution shows multiple peaks close to what could be considered the mean with large number of outliers. Therefore, it is expected that this data would be better described using features more sensitive to these characteristics, so the median and the kurtosis were selected. The final features selected from this process were: mean, median, variance and kurtosis.

Now it was necessary to determine the appropriate number of samples required for calculating those features in a meaningful way. For this system, the E_s/N_o is sampled at 100Hz and the effective channel latency through the channel and receiver equipment was about 40ms, depending on the relative positions of the ground station and SCaN Testbed. It was decided that, at a minimum 4 samples should be used to calculate the features. However, because of the high variance that is experienced during fading, it would be difficult to detect sudden changes over time with such a narrow window. Therefore, it was decided that a window of 1 second (100 samples) would be used to parse the data. This coupled with a

FIFO (first in first out) memory buffer would be sufficient to initialize the model with the first 100 samples and keep enough historical data on the buffer to make an intelligent prediction of the state the link would be experiencing. Finally, this process yielded the following schema for data formatting and feature extraction

1). Raster the data with a window of 100 samples

2). Calculate mean, median, variance and kurtosis for each window.

3). Label each rastered segment based on its class label within the database

The data was processed as described and a database was created with the windowed sections, their features and their corresponding labels. Then, one of the data profiles that contained both Fading and NoFading was removed from the database. This profile can be observed in Fig 3. This profile is used as an independent test case with data the model has never seen, to further evaluate generalization. Then, an 80/20 train/test split was done on the remaining samples and the process moved on to model selection and grid search for hyperparameter optimization.

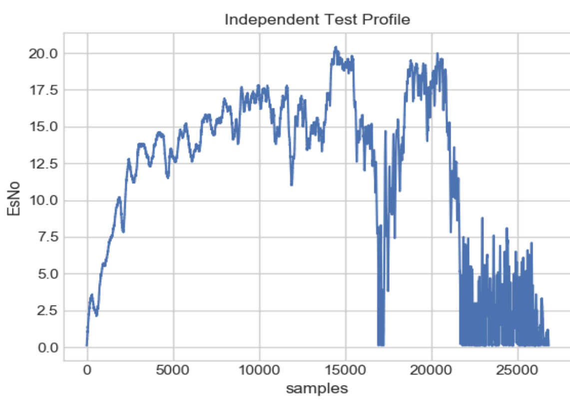

Fig. 3. Data profile used for independent testing for validating generalization.

C. *Model Selection*

Given the data and the formatting that was followed for data exploration and feature selection, it was determined that utilizing kernel methods would be the most appropriate route. Signal processing procedures can benefit from a kernel perspective, making them more powerful and applicable to nonlinear processing in a simple manner [4].

Standard methods, such as correlation to each of the sub-classes and simple thresholds were considered but they yielded poor results when compared to kernel methods. Therefore, a selection of 12 models, including the most common models for kernel methods was taken and applied to the database. Table I, shows the results of this trade study. The models were trained using the 80/20 split (train/test) indicated in the previous section with a further 80/20 on the training set for cross-validation. Then hyperparameter tuning was performed for the Support Vector Machine, Decision Tree Classifier, and the Logistic Regression models.

TABLE I. EXPLORED METHODS

Method Name	***Precision***	***Recall***	***F1-Score***
Naïve Bayes	0.73	0.77	0.75
Linear Discriminant Analysis	0.79	0.76	0.76
Logistic Regression	0.91	0.91	0.91
K nearest neighbor (k=2)	0.68	0.62	0.65
K nearest neighbor (k=10)	0.88	0.88	0.88
K nearest neighbor (k=4)	0.92	0.94	0.93
Support Vector Machine (SVM)	0.94	0.98	0.96
Decision Tree	0.92	0.91	0.91
Learned Vector Quantization (LVQ)	0.78	0.77	0.77
Kernel Regression (Weighted)	0.65	0.69	0.67
Ensemble 1 (SPoC) version 1	0.96	0.94	0.95
Ensemble 2 (SPoC) version 2	0.99	0.99	0.99

SPoC Algorithm Block Diagram

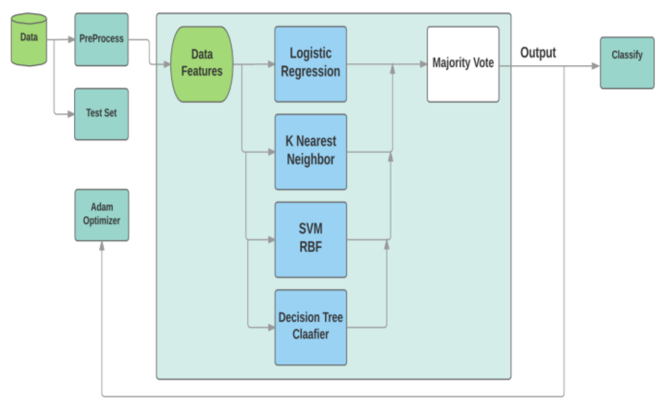

Fig. 4. State Predictor of Classification Cognitive Engine (center) presented within its testing wrapper.

From Table I, it can be observed that the methods which performed the best were: Logistic Regression, K Nearest Neighbor (KNN) with K=4, Support Vector Machine (SVM) and the Decision Tree classifier. However, no single method was able to yield precision and recall metrics above 0.95. Thus, a majority vote classifier method was implemented in an attempt to improve the system. Ensemble 1 is a majority vote between the three top performing models. That is the SVM, the Decision Tree and the KNN with K=4. This yielded results above 0.95 but taking a step further and including every method with metrics above 0.90 yielded the best model, Ensemble 2. Therefore, Ensemble 2 was the chosen method for final assessment with the excluded test data. A diagram of Ensemble 2 or what is denoted as the SPoC Cognitive Engine CE is shown in Fig 5. Note that the Ensemble model is the large green, center box, while the other items are supporting functions for testing.

TABLE II. SPoC Confusion Matrix for Test Set

Confusion Matrix	***Counts***
True Positives	11279
False Positives	214
True Negatives	13514
False Negatives	73

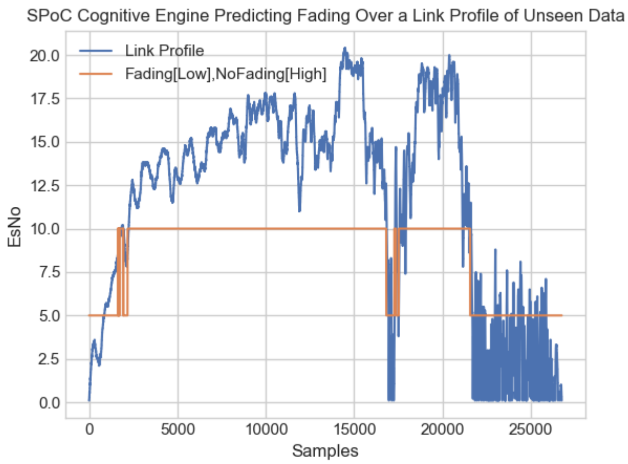

Fig. 5. Running SPoC on an independent test profile for validation using the link emulation testbed.

D. *Algorithm Verification*

SPoC was run using the test data set and the independent profile shown in Fig 4. The results from the test dataset is shown in Table II. As observed, the algorithm was able to correctly classify the test data 99% of the time. The profile in Fig 4 was played back using a link emulator, created to mimic the nuances of the space link for real time testing. It was found that SPoC was able to classify its state correctly and predict the desired action on that state as shown in Fig 5.

III. Results

A. *Testbed Set Up*

Performance of the SPoC CE was evaluated using a laboratory testbed to measure the impact to the overall end-to-end communication system. This process was performed to validate the algorithm within its expected operational environment. The testbed emulates a satellite telemetry DVB-S2 link similar to the SCaN Testbed scenario, and features programmable RF interference, noise, and channel fading. The main hardware components are shown in Fig 6 along with the software components that make use of them.

A channel simulator task applies link impairments based on measurement SNR profiles with SCaN Testbed. A link controller interacts with a DVB-S2 transmitter through a simulated BPSK uplink channel. This transmitter is a SDR chassis running a DVB-S2 waveform that supports on-the-fly configuration of ModCod (modulation-encoding schema), symbol rate, and other parameters. It currently outputs a stream of Pseudorandom Binary Sequence (PRBS) data over the Radio Frequency (RF) link, with optional CCSDS Advanced Orbiting Systems (AOS) framing [5]. This link then passes through a variable attenuator and is split between a commercial DVB-S2 modem and a spectrum analyzer. The variable attenuator is controlled by the channel simulator task and simulates a fading profile on the channel.

In addition, a white noise generator is passed through a variable attenuator, which allows adjustment of the channel noise floor. The receiving modem streams decoded DVB-S2 frames out the "transport bypass" port to the statistics collection task. This task synchronizes to the Attached Sync Marker (ASM) sequence and uses the decoded CCSDS AOS frame counter to infer throughput and drop rates. In addition, this modem streams Received Signal Strength Indicator (RSSI) information, which includes a synchronization lock indicator and estimated Es/No, to the link controller. The SPoC-CE is provided this Es/No estimate and decides of the channel state (fading / no fading).

B. *System Evaluation, Algorithm Validation*

An ACM algorithm was used in conjunction with SPoC to decide which modulation-encoding schema to use based on the Es/No level seen on the channel. When "Fading" is detected by SPoC the system was instructed to pause data transmission, rather than continue to communication and attempt to track the fading. Otherwise, the system uses the recommended MODCOD by the ACM algorithm. Alternatively, the system could be instructed to use MODCOD-1, the most robust modulation and coding pair. In contract to [2], the ACM controller was modified to pause data transmission when the received Es/No was below the lowest threshold.

Three algorithms were chosen for comparison, the baseline ACM algorithm, SPoC with ACM, and ACM-XM. ACM-XM is ACM with an additional 2 dB of extra margin (XM). The margin was selected to match the overall reduction in data throughput by SPoC.

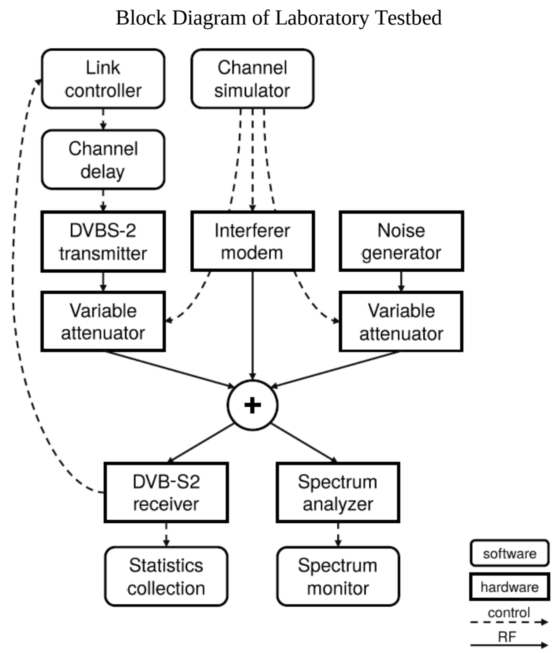

Fig. 6. Laboratory testbed block diagram used to validate SPoC

TABLE III. SPoC VALIDATION & MODEL COMPARISON

Algorithm	***Total Valid Frames***			***Total Dropped Frames***		
	12ms	**40ms**	**500ms**	**12ms**	**40ms**	**500ms**
ACM	16.9e6	16.9e6	16.6e6	7.7e2	3.1e3	3.5e6
ACM-XM	13.3e6	13.3e6	13.2e6	0	0	0.5e6
SPoC	13.2e6	13.2e6	13.1e6	0	23	1.5e6

Table III provides a summary of the results. A total of 29 direct-to-Earth communication events were run, which are representative of operations with SCaN Testbed over a ~2-week period of time. The table shows the total received frame counts and dropped frame counts as a function of channel latency for each algorithm, summed over all events. Compared to the baseline ACM algorithm, there is approximately a 20% reduction in total throughput by using SPoC. Some reduction in throughput is expected, since the system does not attempt to send any data during fading. Some data loss also occurs during false positives, which are rare, but do result in lost potential data throughput.

All algorithms exhibit an increase in dropped frames as the channel latency increases. Although the SPoC and ACM-XM algorithms experienced reduced throughput, both have a substantial improvement in the number of dropped frames. Both the algorithms have negligible dropped frames until the 500ms channel latency test case. At the 500ms channel latency, both SPoC and ACM-XM had substantially less dropped frames. This show that that approach was effective in reducing dropped frames and improving the overall data transfer efficiency.

IV. DISCUSSION

The procedure followed in this study is a blueprint for the use of ML in data processing and creating applications that work with space communication links. The proposed method carries certain benefits for a link controller experiencing this type of channel fading. Currently, there is no method implemented on SCaN Testbed to deal with this fading phenomenon. Therefore, it is best to have a system that detects whether a channel is experiencing high fading and relay that information back to the controller. This way, data transmission can be paused to avoid loss of data.

Developing SPoC as an ensemble of supervised learning models provides the ability to retrain the system and perform hyperparameter tuning in a straight forward manner. Additionally, the different models can be evaluated individually, which makes the system adaptable to different data types and able to generalize very well because of the cancelling variances and biases that each model will have against the other. The data processing and hyperparameter tuning is fully automatic after the initial data pre-processing. These tasks are based on the model's performance against the validation set.

There are some drawbacks to the use of the presented process and SPoC. The most significant drawback is the feature engineering necessary for data processing and labelling. This can affect generalization because the system is dependent on these features to create its predictions, so if those features are biased to begin with, the system will not generalize well outside of the training domain. Another drawback for this approach is the need to have a database with labeled classes ahead of time. There might be applications where such data is not available or not labelled properly for the system to train on.

A system can be envisioned to have "self-labels" based on real time modem statistics, to automate this process of labelling without a human in the loop. Initial efforts in this topic has been done as presented by the Meta Brain for Embedded Cognition Cognitive Engine [6], where features are discovered and then used for classification. The combination of that approach with SPoC can yield a system where dropped frames and other channel statistics with windowing, can be used to block out periods of fading or obstruction.

Overall, the use case of SPoC would allow for links coming from ISS to be shut off if high fading is present. Currently there is no implemented method for detecting this issue on SCaN testbed, so SPoC presents another node for controlling the link. However, elsewhere in the ISS there exists a coverage map that accounts for structure blockage outages. This map is dependent on modelling the motions and structure of ISS. SPoC presents a way of detecting these unfavorable communication periods by analyzing the channel itself, which allows for scaling, independent of structure and motion models of the spacecraft.

The ability to detect channel states has additional advantages for links such as those from ISS to the ground. Such as system can be used to automatically determine appropriate times to transmit data, without requiring manual human intervention to determine the schedule.

This is very useful to avoid clipped frames and other errors derived from high fading. For the purposes of its creation, SPoC would add a good way to manage these SDRs and it presents a relatively simple way of improving the link by not using energy and resources to transmit when the data cannot be decoded on the receiver side. Follow-on testing could involve networking traffic (TCP/IP or CCSDS), which can present a more favorable way to evaluate the network and data transfer efficiency, acknowledgements, retransmissions, and other metrics while using the cognitive engine, to further study it's impact on the end-to-end communications environment.

This paper presents an alternative to standard methods for detecting high fading and it shows how a machine learning model can be used to perform analysis on a communication link from ISS to the ground. There are some benefits and drawbacks to the approach, which should be considered before implementation on a production system.

V. CONCLUSIONS

This study presented the application of machine learning to a space to ground communication link. It was shown that ML can be used to detect the presence of fading in that link, given certain conditions. A detailed description of how the system is able to detect changes in link characteristics was provided and the study presented a process for extracting a target concept from the raw data both a-posteriori and in-situ.

The pre-processing, data exploration and model selection effort were explained in detail. After this, preliminary results were shown, comparing the use of this particular ML method alongside adaptive methods. It was observed that both methods (with and without ML) perform well. Yet, using the ML method, the system was able to reduce the number of dropped frames over the adaptive method (without ML) since SPoC was able to detect fading and change modulation encoding accordingly. It is important to note that the robustness in lack of dropped frames reduces data throughput. Therefore, applications that would implement this method should take that into account.

This study is a proof of concept for using ML in space communications. This study highlights how ML methods can be implemented at the link level of the SCaN infrastructure, presenting both benefits and drawbacks. Ultimately, this work advances NASA's knowledge and understanding of how to use ML technology towards the future of space communications.

ACKNOWLEDGMENT

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