Detection of Malfunctioning Electronic Components via Deep Learning

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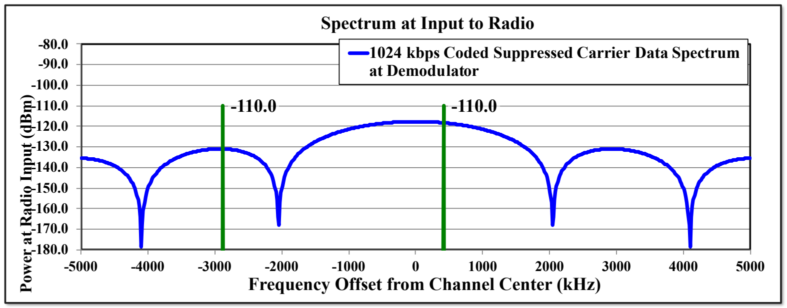
Problem

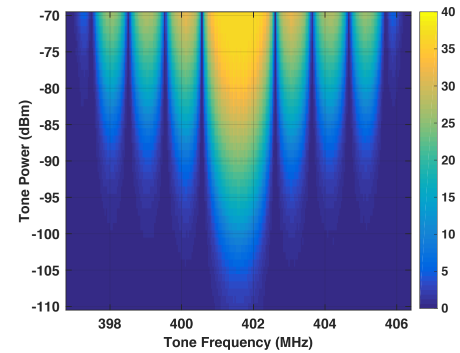
Sources of EMI

- Spacecraft radios are highly susceptible to electro-magnetic interference (EMI) within their operating bands.
- The EMI tone structure is dependent on the exact operating mode of the spacecraft but is stable and repeatable for any one spacecraft operation mode. Thus, the EMI signature forms a spectral "fingerprint" of each operation mode.
- Previous research suggests that these EMI signatures can be used to monitor the status of electronic systems and locate anomalies to individual components.
- In this effort, we use EMI characterization tools to fingerprint nominal behavior of the spacecraft and utilize anomaly detection approaches including auto-encoder networks to detect anomalous EMI signatures that provide early warning of pending component faults or failures.

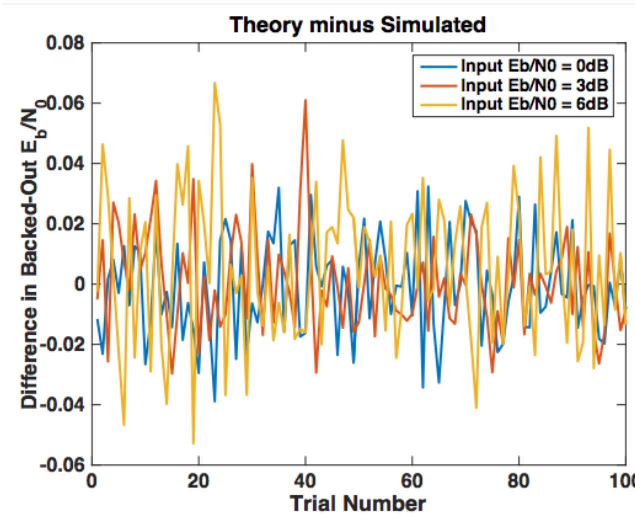
Effect of EMI



EMI induces SNR Loss



- EMI from clocks and power supplies tend to be sinusoidal tones.
- These tones may appear in the modem spectrum, and they will increase the probability of symbol error.
- The probability of error and SNR loss in presence of EMI has been derived analytically.



Modeling of Interference

- The received signal during radio silence is expected to be simply the thermal noise at the low-noise amplifier. However, due to electronic interference onboard the spacecraft, the received signal is instead given by:

$$r(n) = w(n) + \sum_{k=1}^{N} A_k e^{j2\pi f_k n T_s}$$

- where $w(n)$ denotes the thermal noise out of the analog-to-digital-converter (ADC), A_k denotes the complex coefficient of the k-th interfering EMI tone, f_k denotes the frequency of the k-th tone in Hertz, and T_s denotes the sampling period of the ADC.
- The model of $r(n)$ can also cover mechanical vibrations observed by sensors such as accelerometers. The detection of abnormal vibrations (possibly due to improper utilization of equipment or failure of equipment) can thus be covered by our approach.

ESPRIT Algorithm

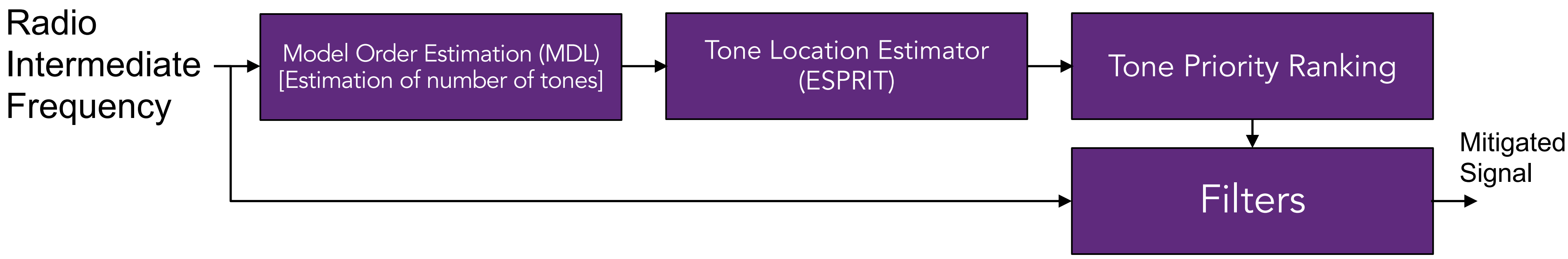
- Previous EMI mitigation effort explored the use of the Estimation of Signal Parameters via Rotational Invariance Techniques (ESPRIT) algorithm for efficiently detecting the frequency, phase, and amplitude (i.e., A_k and f_k) of the incoming signal up to model-order M.

$$\text{ADC} \rightarrow \text{ESPRIT} \rightarrow \{A_k, f_k\}_{k=1}^{M}$$

- The ESPRIT algorithm is much more efficient than the traditional FFT estimation method, where the data sample time and resulting data volume is 1000 to 100,000 times lower than an FFT used on the same signal sample space.
- While this approach allows us to detect the EMI signal parameters, it does not indicate to us when the EMI signature has *changed*. For this reason, we must employ an anomaly-detection algorithm to detect this change. We therefore utilize the ESPRIT algorithm as a feature extractor, and develop an auto-encoder network to detect changes in the EMI signature.

Prior Work: Communication Signal De-noising

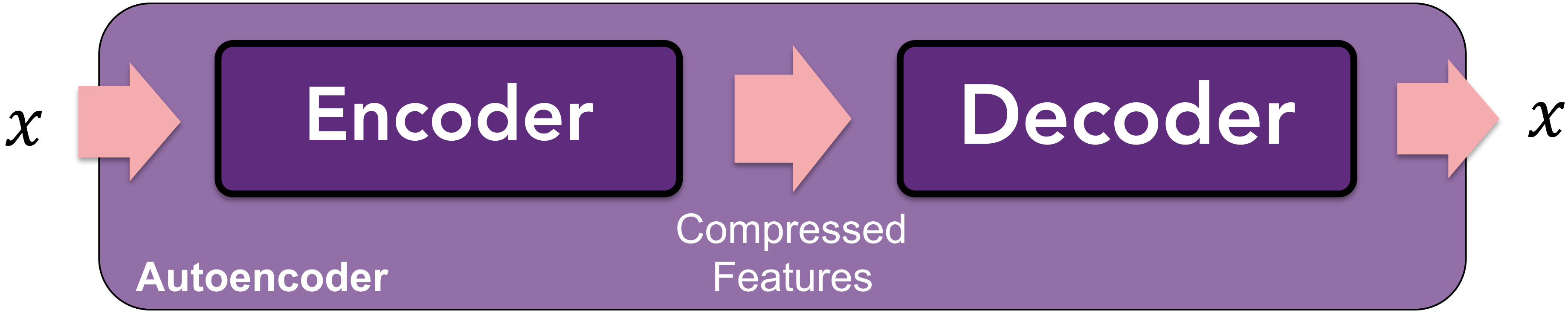
- Given that the ESPRIT algorithm can estimate the tone powers, frequencies, and phases, it is possible to mitigate the effect of the tones on a communication signal:



- The above scheme was implemented on the Iris TRL-9 flight radio.
- Without compensation, the radio is unable to lock to the subcarrier or the symbols. Once the mitigation algorithm is executed, the subcarrier and symbol loops lock. BER testing commenced using a FIREBERD test equipment and indicated 0 BER after mitigation.

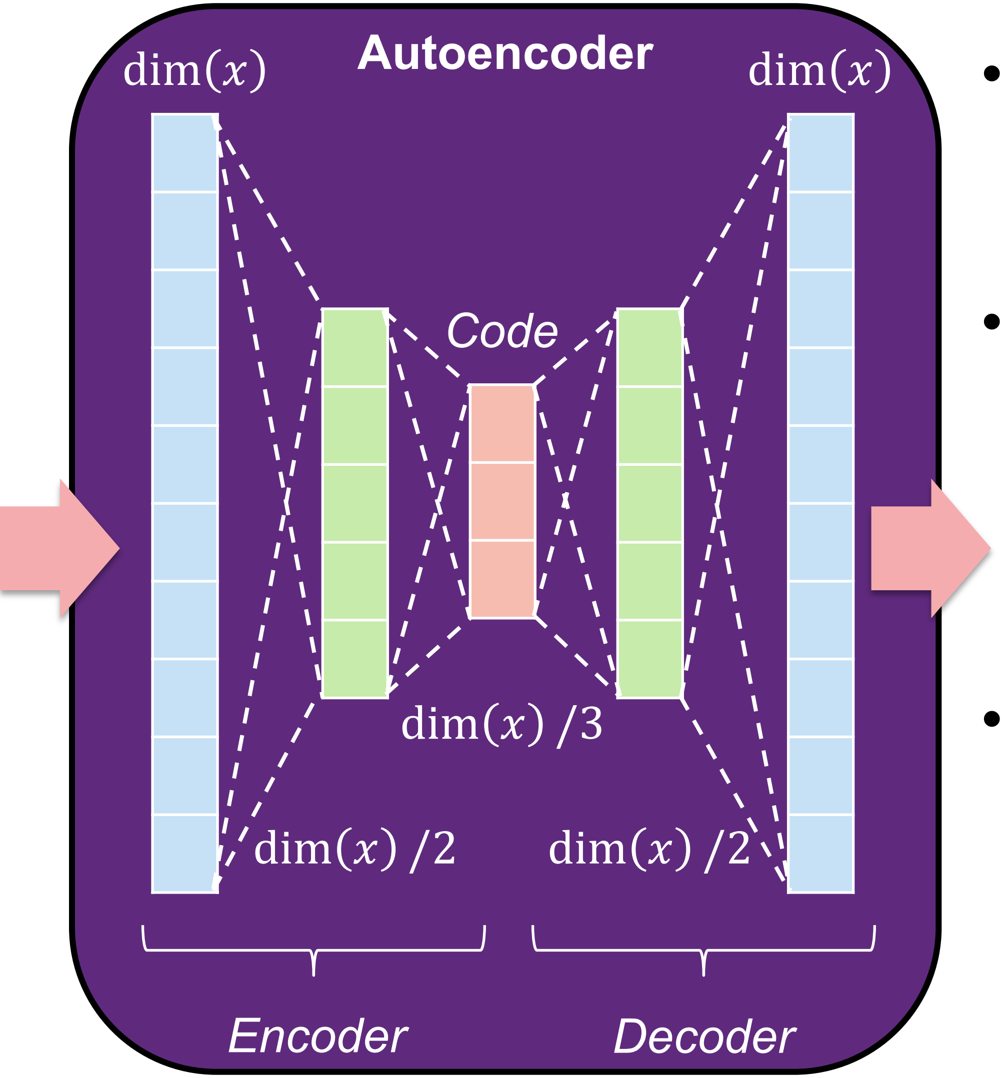
Anomaly Detection and Auto-encoders

- Consider a set of nominal feature vectors $\{x_t\}$. We wish to determine if a new feature vector y is nominal or anomalous.
- Auto-encoders attempts to learn a model that maps the input to itself via compression and de-compression stages:



- If, after learning the encoder and decoder pairs via nominal dataset, the output of the decoder is not close to the input to the encoder, it is assumed that the input is anomalous.

Auto-encoders via Neural Networks



- One way to implement auto-encoders is via Neural networks.
- Fully-connected layers with progressively lower dimensions compress the features to a compressed code.
- Fully-connected layers with progressively larger dimensions decode the code back to the original feature dimensions.

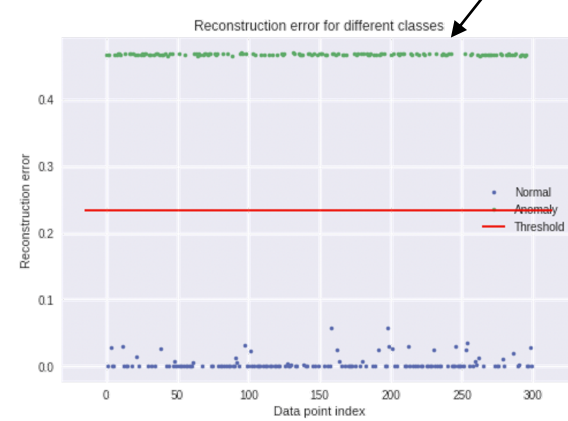
EMI Anomaly Detection Pipeline

- The incoming signal is inherently a time-series signal. In order to transform this into discrete features, we utilize the ESPRIT algorithm.

Autoencoder

ADC → ESPRIT → Encoder (x2) $z = \sigma(W_e x + b_e)$ → Decoder (x2) $\hat{x} = \sigma(W_d z + b_d)$ → L_2 Loss $\|\hat{x} - x\|_2^2 \lessgtr \gamma$

where $\sigma(\cdot)$ denotes a non-linear function such as the rectified linear unit (ReLU) $\sigma(y) = \max(0, y)$.



Current Results

- By running on simulated data with $\mathrm{SNR} = 0\ \mathrm{dB{-}Hz}$ and anomaly change of tone frequency of 1Hz on simulated data, we obtain the following ROC curve:

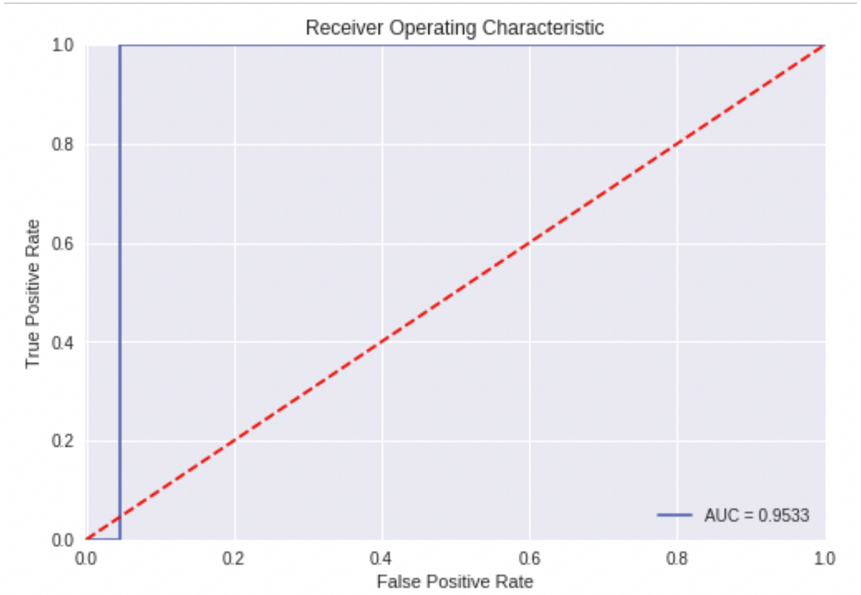


Table I. Confusion matrix for simulated low SNR data and 1Hz anomaly frequency deviation.

	True Normal	True Anomaly
Declared Normal	95.33%	4.66%
Declared Anomaly	4.66%	95.33%

Conclusions and Future Work

- We have shown that an ESPRIT and autoencoder pipeline can be used to detect anomalies in the receiver radio spectrum. This can be used to detect malfunctioning electronic components onboard the spacecraft.
- The ESPRIT algorithm has been shown to be implementable on rad-hard processor parts such as the SPARC processor in previous efforts. The auto-encoder structure is also easy to implement once quantization of the final model is performed.
- Ideally, we would like the anomaly detection scheme to automatically extract the relevant features from the time-series data (as opposed to requiring the use of ESPRIT as a feature extractor). This may require a long-short-term-memory/recurrent-neural-network architecture combined with an autoencoder. Alternative deep anomaly detection algorithms for time-series data may also be utilized such as Multi-Scale Convolutional Recurrent Encoder-Decoder (MSCRED).

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