Executive Summary

DeepSig is developing a suite of revolutionary capabilities leveraging deep learning based signal processing techniques to adapt and excel under a range of difficult operating conditions, mission requirements, and impairment effects. These capabilities offer the potential of significant performance improvements to existing communications systems. Our work so far has been in simulation and lab environments, and we are preparing to move to the next stage of our research – operating in real-world environments. Our application for an FCC experimental license is in support of this research effort.

Technical Background: Autoencoders for Communications Systems

DeepSig principals have developed a fundamentally new approach to the design and adaption of radio communications at the physical layer protocols based on the use of deep learning and a construct called the 'channel autoencoder'. The autoencoder allows the physical layer transmitter and receiver to take the form of mostly unconstrained mappings in a series of efficient parametric linear algebra operations. Using deep learning, we are able to derive a solution to the full communications system design problem by seeking to minimize bit error rate (reconstruction loss). This may be done over a wide variety of channels and impairment models in order to obtain more optimally tailored solutions. By learning physical layer information encoding, decoding, and representation solutions in this end-to-end way, tailored waveforms may achieve novel and unprecedented performance under difficult channel conditions.

Below we illustrate the ability of such a system to achieve capacity curves on par with conventional radio modulation and coding methods under a relatively simplistic Gaussian channel.

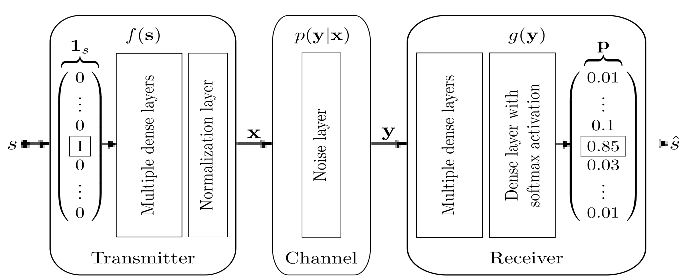
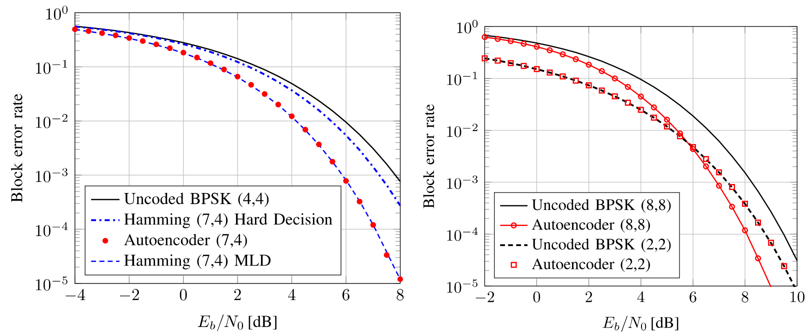
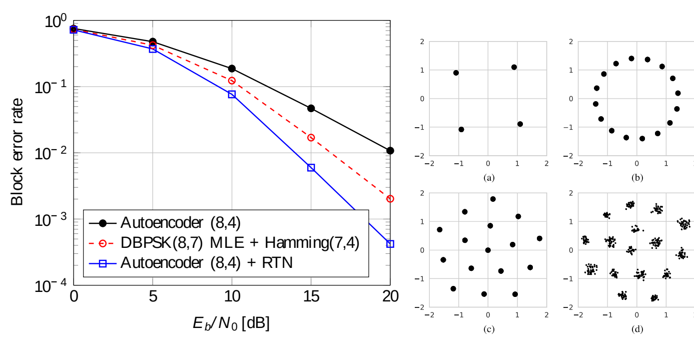


Figure 3 The Fundamental Autoencoder Approach

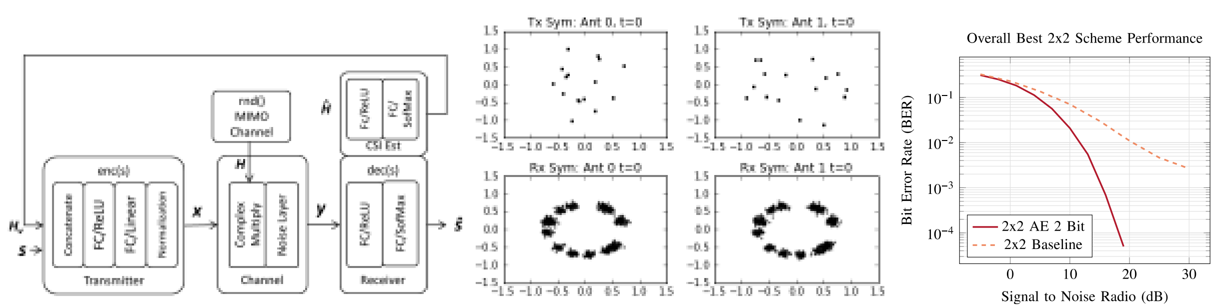


The real benefit of such a system however, is not under the naïve whitened Gaussian channel assumption, but under a series of more realistic systematic impairments which may be modeled and mitigated through adaptivity more richly than thermal noise. Below we show the gains for such a system against a traditional BPSK maximum likelihood decoder with a Hamming code under fading conditions.



Autoencoders with Multiple Antennas

Extending the autoencoder system to the multi-antenna case, we demonstrate that a similar construct can learn to encode information efficiently over a MIMO channel. We show simulation results below for a 2x2 MIMO system.



Description of Experiment

We plan to exercise our ground-breaking approach to waveform design by testing it in a real-world environment – namely, downtown Arlington. We plan to have three fixed antenna locations, and several mobile stations. We also plan to conduct the experiments in a few different frequency bands so that we can evaluate the differences in the machine-learned models with different propagation characteristics. Due to the nature of our experiments, they do not need to be high power, and will not be for long durations.

The below map shows the three fixed points we will use for our experiments, where the red pins indicate the locations as listed in our license application:

Depending on the experiment, we may only use one or two of the fixed locations at a time. Also depending on the experiment, we plan to have up to four mobile transceivers operating between the East and West fixed locations.

The goal of the experiments will be to evaluate the performance of our low-power machine-learned autoencoder-based communications systems in a harsh urban environment.