The purpose of a communication system is to transmit some signal from a source to a destination through a media or channel. While designing a communication system for information transmission, mathematical models are used to characterize the significant properties of physical channels, which in turn helps to design other functional blocks like channel encoder, modulator, channel decoder, and demodulator. To mitigate the distortions introduced by the channel, various functional blocks at the transmitter and receiver have to be designed efficiently. Today’s conventional communication systems are efficiently optimized with the aid of mathematical models and algorithms.

Methodology

A communication system in its simplest form consists of a transmitter that sends a message through a channel which is accepted by a receiver. So the autoencoder which describes a neural network also consists of three main layers each depicting the function of transmitter, channel and receiver. Such an autoencoder can learn full transmitter receiver implementation for a given channel model by minimizing the block error rate (BLER).

An autoencoder neural network of general form Autoencoder(n,k) is designed for uncoded and coded version for BPSK communication scheme. The performance of autoencoder and baseline communication scheme is evaluated in various channel types.

Autoencoder

Autoencoder for different channel types

Autoencoder is trained for different channel types. Autoencoder(n,k) means k bits sent through n discrete use of the channel. BERL vs Eb/N0 for the autoencoder and several baseline communication schemes is evaluated in various channel types.

Autoencoder for Channel having Additive White Gaussian Noise

In AWGN or wireline channel BER decreases exponentially as SNR increases. The figure 4 shows that the autoencoder is able to achieve a performance of soft decision hamming decoder (7,4). The figure 5 shows that an autoencoder (8,8) is able to achieve a performance much better than traditional uncoded BPSK (8,8) and autoencoder (2,2) achieved a performance similar to traditional uncoded BPSK (2,2).

Autoencoder for Channel having Rayleigh Fading

BER in the fading channel decreases linearly as SNR increases. In channels with both fading and AWGN noise more signal power is needed to achieve the same BER as in AWGN channel. Autoencoders were trained at an SNR of 7dB and different learning rates were used for optimizing the SGD algorithm for minimizing the block error rate. As SNR increased autoencoder performance improved compared to the traditional systems. The figure 6 shows that autoencoder (7,4) is able to achieve a performance similar to Hamming soft decision decoder at the receiver. The figure 7 shows that autoencoder (2,2) is having better performance than traditional uncoded BPSK (2,2). Autoencoder (8,8) performs better only at high signal to noise ratio.

Autoencoder for Channel having Double Exponential Noise

Autoencoders were trained with different learning rates at a fixed SNR of 7dB to optimize the SGD algorithm which is intended to minimize the BLER. Autoencoders gave lower BLER at high SNR compared to the computer aided simulation of traditional systems using Monte-Carlo simulation. Figure 8 and 9 shows that the performance of the autoencoder is truly better than the traditional system.

Autoencoder for Channel having Cauchy Noise

The figures 10 and 11 show that autoencoder performance is worse in the presence of cauchy noise compared to traditional systems. From the figure it is clear that even though bit error rate decreases as SNR increases, the decrease in bit error is very low compared to the presence of other noises like AWGN and Laplace noise in the channel. Autoencoder model was trained at a fixed SNR of 7dB. In order to learn the patterns of the received signal, receiver layers in the autoencoder can be increased and also various other neural networks like convolutional neural network (CNN), recurrent neural network (RNN) can be tried to get a better autoencoder model.

Autoencoder for Channel having Contaminated Gaussian Noise

From the figure 12 and 13 it is relevant that the autoencoder failed to perform well in the presence of contaminated Gaussian noise. There is a slight decrease in bit error rate as SNR increases, but compared to the Monte-Carlo Simulations bit error rate is high.

Analysis and Results

Some of the options that can increase the performance of the autoencoder model are training the autoencoder at different SNR, including more transmitter and receiver layers for the autoencoder, different neural networks at each layer of the autoencoder model and a balanced training sample to train the optimal autoencoder model.

Summary/Conclusions

The proposed Autoencoder failed to perform well in the presence of cauchy and contaminated gaussian noise channels. Other types of neural networks like CNN, RNN etc can be considered to improve the performance of autoencoder by incorporating those into the different layers of the same. The autoencoder was trained only at a particular SNR, if the training include more SNR, it can perform better while testing.

Using an autoencoder, an end to end communication system is realized that emulates transmitter and receiver roles without any advanced knowledge. Such neural network systems evolve to give their best as technology advances. Trained Neural networks are not better for scenarios having existing optimal algorithms.

Key References


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