COGNITIVE DIVERSITY EQUALIZATION FOR 2X2 HF MIMO CHANNELS

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ABSTRACT

The ionosphere has been both a hindrance and attraction of communication solutions that require usage of the High Frequency (HF) band for propagation. While the ionosphere is able to propagate signals at long ranges, it can also introduce significant distortion via multipath and fading. One approach investigated by works in the literature as a means of helping improve communications in the HF band has been the usage/design of MIMO systems. Cognitive equalization can be used to further help mitigate these issues by using reinforcement learning to determine the optimal equalizer configuration (i.e. tap length, filter type, etc.) for a specific channel. The objective of this paper is to investigate the performance of cognitive equalization for a simulated 2x2 HF MIMO channel when the Epsilon-greedy and Softmax Strategy algorithms are used to learn the optimal equalizer structure when having access to Linear and Decision-Feedback equalizers in diversity mode.

INTRODUCTION

The main feature of the High Frequency (HF) band (3-30 MHz) is enabling the usage of the ionosphere to propagate long-range communications. This is ideal for applications that require long-range wireless solutions to operate with low costs. However, one of the main difficulties of operating in the HF band is that the ionosphere is also notorious for experiencing frequent fluctuations and causing significant distortion (i.e. multipath, fading, etc.). This has motivated research in applying techniques from signal processing and machine learning to mitigate these effects to make the band more reliable. Examples of these areas include frequency selection [1], channel sounding [2], and equalization [3].

An additional area of research that has been explored in literature is the usage/design of HF MIMO systems. The following are some examples from the literature. Co-located antennas have been presented as a means of facilitating the implementation of HF MIMO systems (e.g. [4] [5]) A full physical layer outline for a 2x2 HF MIMO system to improve the functionality of an HF military standard (MIL-STD-188-110C Appendix D) is proposed in [6]. [7] presents an analysis on how errors incurred from Minimum Mean Squared Error (MMSE) channel estimation can affect the throughputs obtained by an HF MIMO-OFDM system. In [8], a long short term memory (LSTM) network is configured for online learning to perform channel estimation in a 2x2 HF MIMO system and is shown to be highly effective.

In this work, we apply the concept of cognitive equalization for 2x2 HF MIMO channels. Cognitive equalization refers to the concept of using reinforcement learning to determine the optimal configurations (i.e. tap length, step size, adaptive algorithm, filter type) for an equalizer for a specific channel. Cognitive Engines (CEs) are used to facilitate this learning of the optimal equalizer settings. A CE is used to accomplish this because it "is an intelligent agent which observes the radio environment and chooses the best communication settings that meet the application's goal" [9]. Whereas in previous works CEs have been used at the transmitter to learn optimal transmission parameters (e.g [9] [10] [11]), when implementing cognitive equalization, CEs are used at the receiver. We have previously employed our cognitive equalization techniques in a single input single output (SISO) context for HF channels in [12] and [13]. In this work, we analyze the performance of these techniques in a MIMO setting, under different HF channel conditions. We also assume that diversity mode is being operated, where each stream generated on the transmit side consists of the same data.

A similar topic was covered in [14] where two approaches were presented for finding the optimal equalizer configuration for HF MIMO channels when having access to a zero-forcing equalizer, MMSE equalizer, and the Maximum Likelihood technique. The first approach identifies the equalizer that attains the lowest bit error rate (BER) and uses a genetic algorithm to learn the optimal equalizer parameters for it. The second approach uses brute force to identify the equalizer that attains the lowest BER and then uses Q-learning to continuously adapt the equalizer's parameters to obtain additional performance improvements. If the BER of the equalizer exceeds a certain threshold, the approach then starts over. In this work, different algorithms are used for learning the equalizer parameters and they do not identify the best equalizer first but attempt to learn over time which of the available equalizer settings provide an optimal performance for the given channel. Additionally, this work uses two equalizers (linear and decision-feedback) in diversity mode whereas [14] uses them in spatial multiplexing mode (i.e. the streams of data sent on both antennas are distinct). Lastly, instead of using BER as the feature for characterizing options, we use a feature called the average minimum distance, which will be explained later.

This paper is structured as follows: First, background is provided on the cognitive engines used in this work. Then, the equalizers used in this work are explained. Afterwards, the structure of the simulations performed in this work is described, and an analysis of the results obtained from these simulations is presented. Finally, the results from this paper are summarized and future directions are also discussed.

COGNITIVE ENGINES

In this work, we use reinforcement learning algorithms to function as CEs. The purpose of reinforcement learning is to help a user (often referred to as an agent) learn how to achieve a certain objective. Specifically, rewards are used/assigned based on a particular action chosen to help the agent determine which actions can best accomplish this objective. The goal of reinforcement learning is to manage an effective balance between exploring and exploiting so that the best set of actions can be determined optimally. Exploring refers to choosing a new action, and exploiting refers to choosing the best action out of the ones explored [10]. The following is an overview of the CEs used in this work.

A. Algorithms

The ϵ-greedy algorithm is a simple approach to solving this problem. Under this technique, an agent will explore with probability ϵ and exploit with probability $1-\epsilon$ [15]. The Softmax Strategy, however, initially assigns each available action an equal probability of being used. It then uses the rewards an action obtains to either increase/decrease the probability of it being chosen [15]. The probabilities are calculated as shown [9]:

$$P_k = \frac{e^{\overline{\mu_k}/T}}{\sum_i e^{\overline{\mu_i}/T}} \tag{1}$$

where P_k represents the probability of choosing the k^{th} action, $\overline{\mu_k}$ represents the average reward obtained by the k^{th} action, and T (referred to as the temperature) manages how much exploration/exploitation is performed. Specifically, a higher value of T corresponds to more exploration while a lower value of T corresponds to more exploitation [15].

B. Rewards

In efforts such as [9] and [11], the objective of the CEs have been to maximize throughput. This makes sense because in these works, the CEs have been employed to find optimal transmission configurations. In this application, and in our previous publications on cognitive equalization [12][13], the CEs are implemented at the receiver with the objective of minimizing errors. To make this objective achievable, the metric used as the reward in this effort is a unit called the average minimum distance. This value is calculated by recording the distances from the received symbol to the symbol assigned by the slicer, taking their sum and then dividing it by the number of bits processed. Thus, like in our previous efforts [12][13], the CEs are tasked with finding the equalizer configurations that minimize the average minimum distance.

DIVERSITY EQUALIZERS

This work assumes a 2x2 HF MIMO system operating in diversity mode, meaning that each transmitter sends the same data in order to reduce the measured BERs. It's also assumed that the CEs have access to two equalizers, linear and decision-feedback (i.e. DFE), operating in diversity mode. This section specifies how these two equalizers are implemented in this work.

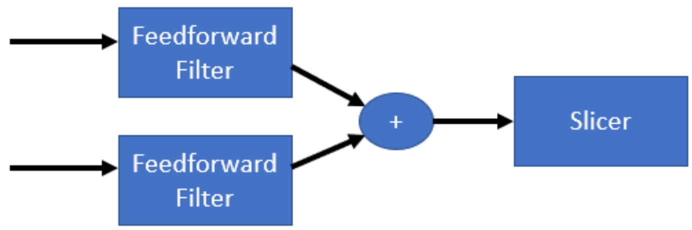

Figure 1: Abstracted representation of Diversity Linear equalizer in the case of 2 antennas proposed in [16]. Original image/full representation can be found in [16]

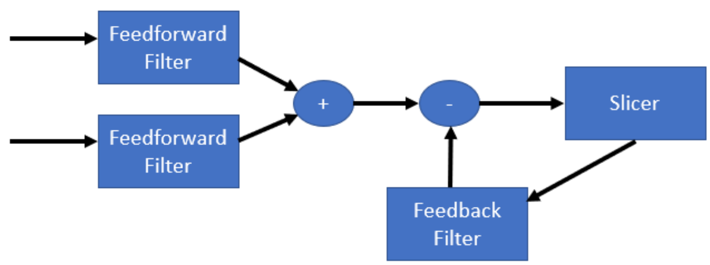

Figure 2: Abstracted representation of Diversity DFE in the case of 2 antennas proposed in [18]. Original image/full representation can be found in [18]

C. Linear Diversity Equalizer

The linear diversity equalizer used in this work is based on the design proposed in [16]. Figure 1 outlines how the linear diversity equalizer is implemented for the case of two antennas in this work. Essentially, each receiver acts as a separate feedforward filter and processes one of the two incoming streams. The outputs of the two filters are then summed and passed to the slicer to make a decision as to what symbol the resulting value should be assigned to. The authors of [16] also specify that the weights of the filters can be adjusted using an adaptive algorithm. While [16] considers a delay in the training sequence, for ease of simulation, we do not.

D. DFE Diversity Equalizer

A DFE configures a slicer to make decisions on the difference between the outputs of a feedforward filter and a feedback filter, where the feedback filter is used to process prior decisions made by the slicer [17]. The diversity DFE used in this work is based on one of the designs proposed in [18]. Figure 2 outlines how the diversity DFE is implemented for the case of two antennas in this work. A feedforward filter is used for each incoming stream; however, only a single feedback filter is used in the equalizer. The outputs of the feedforward filters are summed together while the output of the feedback filter is subtracted from this sum. This result is then passed into the slicer. The authors of [18] also specify that the weights of the filters can be adjusted using an adaptive algorithm.

NUMERICAL RESULTS

E. Setup

In this section, we present results on simulations of our cognitive equalization techniques in a 2x2 MIMO channel under different HF conditions. The CEs were implemented in Matlab as well as the equalizers [15][17][19] [20]. To simulate the HF channel, a built-in model available in Matlab was used. The model is a standardized version of the Watterson Model [21]. These channel conditions were then fed into Matlab's built-in MIMOchannel function to simulate a 2x2 HF MIMO Channel. The sampling rate is set to 6400 Hz, and it's assumed that there is no spatial correlation between the antennas. The HF channel conditions used in this work are summarized in Table 1.

Table 1: ITU Channel Model Specifications from [22]

Channel Condition	Delay Spread	Frequency Spread
Mid Latitude, Quiet (MQ)	0.5 ms	0.1 Hz
Mid Latitude, Disturbed (MD)	2 ms	1 Hz

Baseband BPSK modulation was assumed for all experiments. 1000 frames were sent for each SNR. Each frame consisted of a training sequence and testing sequence that each contained 500 symbols. A $\frac{1}{2}$ rate convolutional code was applied separately on the training and testing sequences. Each of the cognitive engines had a choice of linear and decision-feedback diversity MIMO equalizers. Additionally, each of the cognitive engines have a choice of using either the Least Mean Square (LMS) or Recursive Least Squares (RLS) algorithms for adapting the weights of the equalizers. The step sizes/regularization factors available for each configuration are 0.01, 0.001, and 0.0001. The forgetting factor for each of the RLS configurations is fixed at 0.99. As for the CEs, ϵ was set to 0.1 and T was set to 0.01. The tap lengths that the CEs could choose ranged from 10 to 60 in increments of 5 (i.e. 10,15,20,...). Each filter in the same equalizer configuration used the same number of taps (i.e. for a choice of a decision feedback equalizer, each of the two feedforward filters and the feedback filter had the same number of taps). Additionally, each filter in the same equalizer configuration used the same step size/regularization factor (i.e. for a choice of a decision feedback equalizer, the two feedforward filters and feedback filter used the same step size/regularization factor listed in that specific configuration).

All of these different attributes resulted in the CEs having a choice of 132 configurations. Zero-padding was also assumed for all equalizers when processing the testing sequences. Each of the results compare the CEs to a "fixed" equalizer, where we mean that the equalizer is still adaptive (i.e. weights can be learned) but its structure cannot change. The fixed configuration consists of having 10 feedforward taps, 10 feedback taps (in the case of a DFE), and a step size/regularization factor of 0.01. Four fixed configurations are considered in each of the simulations: an LMS diversity linear equalizer, LMS diversity DFE, RLS diversity linear equalizer, and RLS diversity DFE. These configurations are also included in the set of possible options for the CE to select. The performance of the CEs for the first 500 frames at each SNR was not recorded in order to give them

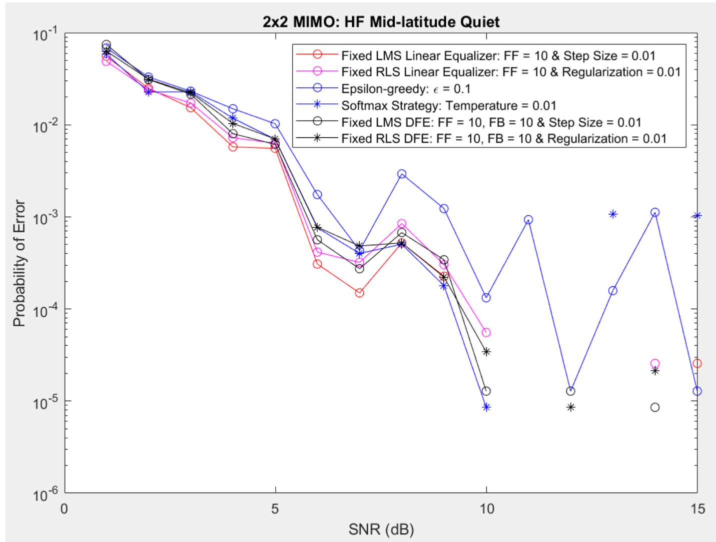

Figure 3: Performance of cognitive equalizers for Mid-Latitude Quiet Channel

a chance to learn what the optimal choices were. To be consistent, the performance of the fixed equalizers were also not recorded until after the 500^{th} frame at each SNR.

F. Analysis

Figure 3 shows the results of the fixed and cognitive equalizers for the Mid-Latitude Quiet channel. The figure indicates that at higher SNRs, the Softmax Strategy CE is able to attain comparable performances to the fixed LMS and RLS diversity equalizers, with the exception of 12.9897 and 14.9897 dB. At lower SNRs, the Softmax Strategy is also able to attain a comparable performance to the fixed equalizers, with the exception of 3.9897, 5.9897 and 6.9897 dB for the Softmax Strategy. However, the CEs are selecting their configurations without any prior knowledge of the channel. Thus, the fluctuations in their performance may be due to the exploration cost incurred when trying out different equalizer configurations. Additionally, in this channel, it seems that the ϵ-greedy CE seems to generally have the worst performance of the cognitive engines and the fixed equalizers. This implies that as a result of ϵ being set to 0.1, to do more exploitation, the CE seems to be stuck frequently on suboptimal options. This indicates that the value of ϵ may need to be strategically adjusted to ensure a better performance. One possible method to improve this would be to use the annealing version of the epsilon greedy algorithm (as used in [11]) where the value of epsilon gradually decreases from a relatively high value (approximately 1) to a low value to encourage more exploration initially and more exploitation as time progresses. This is left as a future task.

Figure 4 shows the results of the fixed and cognitive equalizers for the Mid-Latitude Disturbed channel. The figure indicates that the fixed equalizers, which are the same fixed configurations used in Figure 3, attain a worse performance due to the channel quality degrading. However, the two CEs are able to attain performances better than the fixed equalizers in this channel. This indicates that the CEs are able to select configurations that outperform the fixed equalizers. Figure

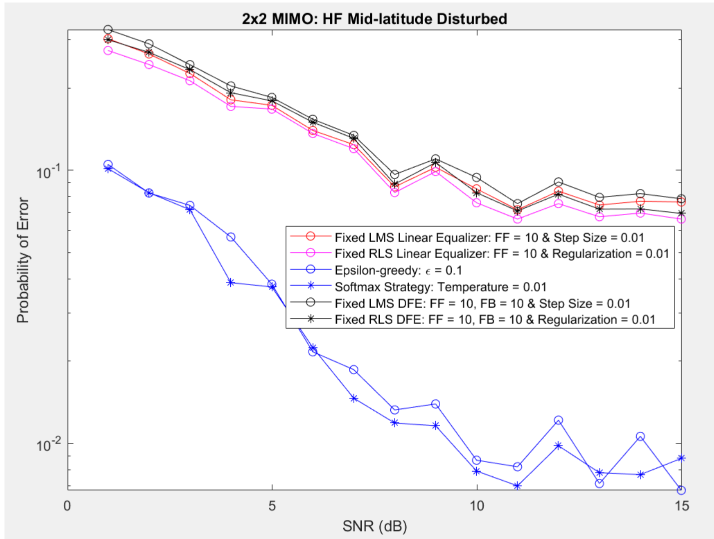

Figure 4: Performance of cognitive equalizers against fixed equalizers for Mid-Latitude Disturbed Channel

4 also indicates the motivation for employing cognitive equalization. Albeit the CEs could only obtain a performance close to the fixed equalizers in the Mid-latitude Quiet channel, which does not have a significant amount of distortion (see Table 1), Figure 4 indicates that in a more degraded channel the CEs are able to learn more effective configurations while the performance of the fixed equalizers are significantly degraded. This shows the need for being able to modify an equalizer's structure (i.e. tap lengths, step size, adaptive algorithm, filter type), in addition to the actual values of its weights. Additionally, the CEs are able to attain this performance without any prior knowledge about the channel.

It's interesting to note that the linear diversity equalizers seem to consistently outperform the diversity DFEs in the Mid-Latitude Disturbed channel. Specifically, the LMS and RLS linear equalizers outperform the LMS and RLS DFEs respectively. Additionally, in the Mid-Latitude Quiet channel, a similar trend (with some exceptions compared to the Mid-latitude Disturbed channel) can also be observed. Further investigation is needed to determine why this is occurring.

CONCLUSIONS

In this paper, an analysis was presented on using reinforcement learning to determine the optimal settings for an adaptive equalizer for 2x2 HF MIMO channels, operating in diversity mode. The results indicate that in good channel conditions, the CEs may struggle more to attain comparable performance. However, as the channel quality degrades, the CEs are able to determine equalizer configurations that obtain a better performance compared to an adaptive equalizer that cannot change structure. This is also considering that the CEs are not using any a-priori knowledge about the channels to make decisions. Future work will include implementing equalizers that operate in spatial multiplexing mode, where each transmitter sends a different stream of data to increase throughput, and incorporating them as choices that the CEs can access. An additional objective will be to observe if machine learning methods can also be used to improve channel estimation in the HF band.

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