COGNITIVE EQUALIZATION FOR HF CHANNELS

Noel Teku

* University of Arizona, Electrical and Computer Engineering Dept.

Tucson, AZ, 85721

[nteku1, tbose]@email.arizona.edu

Faculty Advisor:

Dr. Tamal Bose

ABSTRACT

In the High Frequency (HF) band, ranging from 3-30 MHz, long-range communications can be obtained by bouncing signals off the ionosphere without any significant infrastructure. However, the ionosphere changes rapidly, which can cause potentially harmful effects to the transmitted signal. This has motivated research into using adaptive equalization in this band to reverse these effects. However, a disadvantage of this technique is that based on the equalizer model and learning algorithm used, the error propagation may become significantly large, resulting in insufficient equalization to respond to these variations. To counter this, we investigate the usage of cognitive equalization, where an adaptive equalizer is equipped with the ability to change its structure (i.e. number of taps, step size, etc.) based on the current channel conditions and use probability of error to characterize its performance.

INTRODUCTION

In the High Frequency (HF) band, ranging from 3-30 MHz, long-range communications can be obtained by bouncing transmitted signals off the ionosphere without any significant channel infrastructure (i.e. satellites, cell towers). This lack of equipment leads to further benefits; such as, low-cost communications and portable systems. In [1], we showed that an HF receiver, consisting of a software-defined radio, HF antenna and matching circuit, was capable of observing long-range communications by being able to hear from multiple distant locations including Tokyo, Japan. Because of these reasons, the HF band has been a popular band of interest for a broad range of applications and has often been viewed as a back-up for communication systems in the event of an adversarial attack [2]. HF radios have also been used during emergency crises, in place of mainstream communication systems that may be significantly damaged [3]. In addition, because of their portability, HF systems have been commonly used by the military to feasibly transmit in treacherous locations [4].

However, the ionosphere is very unstable and can vary based on multiple factors including "the time of day, location, and current season" [5]. These variations can cause harmful effects to the transmitted signal, such as multipath and fading. Thus, different signal processing techniques must be implemented at the receiver to counter these time-varying channel effects. One such technique that can be used is adaptive equalization, where the taps of an equalizer are adjusted based on the incoming signal via a learning algorithm (i.e. Least Means Squares, Recursive Least Squares, etc.). There has already been a large amount of research in using adaptive equalization in the HF band. However, based on the particular equalizer used, the algorithm may be prone to significant error propagation — to the extent where the taps are no longer able to accurately reverse the channel effects. In addition, due to the frequent ionospheric variations, it may be possible, for example, that an equalizer with fewer taps may be sufficient — enabling a lower computational complexity to be obtained compared to an equalizer with a high number of taps.

Thus, in this paper, we introduce the concept of *cognitive equalization* as a means of improving the effectiveness of adaptive equalizers. We use cognitive equalization to vary the tap length and step size of an adaptive equalizer based on the current channel conditions. These potential combinations of tap lengths and step sizes are determined using a *cognitive engine* (CE), "an intelligent agent which observes the radio environment and chooses the best communication settings that best meet the application's goal" [6]. The CE is implemented in software and used at the receiver so that the above attributes of the equalizer can be adjusted if the current configuration is not capable of compensating for impairments caused by the channel. The structure of the paper is as follows: first, we provide background on Decision-Feedback Equalizers (DFEs), the Least Means Squares [LMS] algorithm, CEs, and the Watterson Model — a common model used for HF simulations. We then discuss the setup of our experiments comparing the effectiveness of a cognitive and *preset* (i.e. fixed tap-length and step size) LMS-DFE and provide an analysis of the results. Lastly, we summarize the work completed in this effort and describe future objectives.

BACKGROUND

A. Decision-Feedback Equalization

There are two main kinds of equalizers: linear and nonlinear. The main distinction between when an equalizer from either category is used in a particular situation is dependent on the amount of inter-symbol interference (ISI) present in the channel. For the case where a channel has severe ISI, a linear equalizer will end up amplifying the noise, but the nonlinear equalizers are structured to remove it [7]. A DFE is an example of a nonlinear equalizer, and its general structure is shown in figure 1 [7]. The feedforward and feedback filters are both linear filters and need not have the same tap length or step size. The purpose of the feedback filter is "to eliminate the ISI caused by previously detected symbols on the current symbol to be detected" [7]. The detector takes as input the difference between the feedforward and feedback filters and assigns it a value based on a particular metric (i.e. minimum distance) and the expected modulation. If BPSK was used, for example, then the detector would determine whether or not the incoming values were 1 or -1. A standard formulation of a DFE is:

$$\hat{I}_k = \sum_{j=-K_i}^{0} c_j v_{k-j} + \sum_{j=1}^{K_2} c_j \check{I}_{k-j} \tag{1}$$

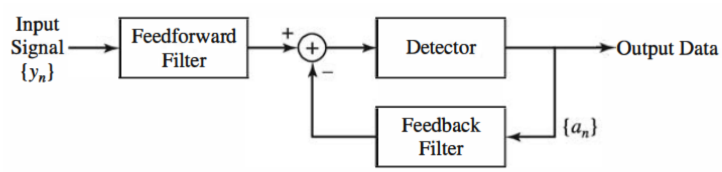

Figure 1: Typical DFE Structure - from [7]

where c_j represents the taps of the DFE, v represents the sequences received from the channel, $(K_1 + 1)$ and K_2 are the number of taps of the feedforward and feedback filters respectively, $\check{I}$ represents symbols decoded in previous iterations, and $\hat{I}_k$ represents the output of the equalizer [8]. In equation 1, the first summation represents the feedforward filter and the second represents the feedback filter.

Two common modes of operation for equalizers are reference-directed and decision-directed [9]. In reference-directed mode, a small portion of data — referred to as a training sequence — is sent to an equalizer to enable its taps to be adjusted using a learning algorithm prior to transmission of the actual (i.e. testing) data. This is done to reduce the probability of the equalizer making errors but comes at the cost of sending symbols to train instead of the actual data. Once this training phase is complete, the equalizer will transition into decision-directed mode, where the taps derived from the training session are now frozen. The testing data is then sent to the equalizer, which is now only able to use the frozen taps to remove any impairments in the received signal.

B. LMS Algorithm

As stated in Section A., a DFE can be adaptive if a learning algorithm is used to update the weights of the feedforward and feedback filters. One such algorithm that can be used is the LMS algorithm, which is derived as follows [10]. First, the output of the equalizer is determined as

$$y(n) = \hat{w}^H(n)u(n) \tag{2}$$

where $\hat{w}^H$ represents the estimate of the ideal weight vector, H represents the Hermitian transposition, and $u(n)$ represents the input vector. Once $y(n)$ is obtained, if the desired signal is known at time step n, the error can be obtained using

$$e(n) = d(n) - y(n) \tag{3}$$

where $d(n)$ is the desired signal. The objective of the LMS algorithm is to determine the weight vector that minimizes the following cost function:

$$J(n) = E[|e(n)|^2] \approx e(n)e^*(n) \tag{4}$$

where E represents the expectation. The approximation in equation 4 is made because having the taps adapt based on the current value of $e(n)$ is more effective in modelling channel variations compared to performing an average [10]. To find the subsequent tap vector that is most effective in optimizing the above cost function, the following equation is used to update the taps at each iteration of the adaptation process:

$$\hat{w}(n+1) = \hat{w}(n) + \mu u(n)e^*(n) \tag{5}$$

where μ represents the step-size. Thus, the LMS algorithm can be used for updating the weights of the DFE.

C. *Cognitive Engines*

As stated in the introduction, CEs are used to determine the optimal communication parameters for a radio based on the current channel conditions. However, the search space a CE will parse through in order to find such parameters (i.e. modulation, coding, antenna technique, etc.) may be significantly extensive. In most applications, the radio will not have the luxury of time to try each option to determine which set is optimal [11]. However, if the radio only selects the best option out of the options it has always tried, it may never utilize a potentially better configuration. This is the classic problem of *exploration* vs. *exploitation*. Exploration is the process of randomly selecting an option; however, exploitation is the process of using the best option out of the options that have already been explored [11]. In order to find this balance, we implement CEs through the framework of *reinforcement learning*, a subset of machine learning where the objective is to determine the best set of actions that maximize/minimize a particular objective.

Reinforcement learning algorithms train a model by sending it rewards based on the actions taken. Rewards are "measure[s] of success" [12] and are determined based on their relationship to the objective being maximized/minimized. Some examples of rewards within the realm of communications include maximizing throughput and minimizing bit error rates (BER). Similar to [6], we assume that each option's ability to obtain a reward is characterized by the estimated average of the reward distribution (i.e. calculated based on how many times the option has been used). In summary, CEs use reinforcement learning to find the optimal transmission parameters that maximize/minimize a certain objective. For this paper, an ϵ-greedy CE is implemented, where exploration occurs with probability ϵ, and exploitation occurs with probability $1 - \epsilon$ [12].

D. *Watterson Model*

As stated in the introduction, the Watterson model is the most commonly used model for simulating ionospheric effects on HF transmissions. In [13], Clark Watterson introduced the model and verified it using over-the-air measurements. Watterson depicts the ionosphere as a tapped delay line, with each tap modulating a delayed version of the signal in both amplitude and phase, as shown in figure 2 [14]. Each tap of the delay line has a bivariate Gaussian distribution

$$G_i(t) = G_{ia}(t)e^{j*2*\pi*v_{ia}*t} + G_{ib}(t)e^{j*2*\pi*v_{ib}*t} \tag{6}$$

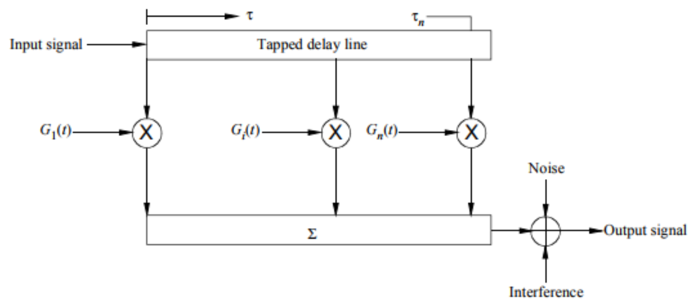

Figure 2: Watterson Model - from [14]

where a and b represent the magneto-ionic components, $G_i(t)$ represents the tap-gain function, $G_{ia}(t)$ and $G_{ib}(t)$ represent bivariate Gaussian distributions, and v_{ia} and v_{ib} represent Doppler shifts [14]. Watterson's work also verified that one consequence of using the HF band is the transmitted signal being susceptible to Rayleigh fading. However, to obtain this model, Watterson assumed that the channel was stationary in time and frequency, making it only sufficient for small bandwidths [13]. The International Telecommunications (ITU) has published a standardized version of the Watterson model across different channel conditions [14]. The ITU's version of the Watterson model consists of a "tapped delay line with only two taps... The taps are fading independently with a Rayleigh (i.e. complex Gaussian) probability density function and a Gaussian fading spectrum" [15]. The ITU recommended channel models used in our experiments are listed in table 1.

NUMERICAL RESULTS

In this work, we compare the performance of a preset LMS-DFE with our cognitive equalization technique. Matlab was used to simulate the ITU channel models and implement the LMS-DFE [7]. We assume BPSK modulation is used and implement the detector of the DFE to assign the incoming values as BPSK symbols. Based on the current HF military standards, as summarized in [16], we assume a sample rate of 6400 Hz for the simulations.

The objective of the ϵ-greedy CE was to determine the tap-lengths of the feedforward and feedback filters, and the step size of the DFE that would minimize the probability of error. The ϵ-greedy CE uses the average minimum distance (i.e. sum of the minimum distances in reference to the symbols of the BPSK constellation divided by the length of a full testing sequence) as a basis for distinguishing between the configurations. As explained in Section C., when the ϵ-greedy CE explores it will select an equalizer configuration randomly. However, when it exploits, the equalizer configuration with the smallest error rate, represented by the average minimum distance, will be chosen. When a configuration is selected, its average minimum distance is updated.

For simplicity, it was assumed that the feedforward and feedback filters were implemented with the same step sizes for each option selected. The selection of feedforward taps varied from 5-25 taps, and the selection of feedback taps varied from 7-14 taps. The different step size values that could be selected were 0.01, 0.001, 0.0001, and 0.00001. This resulted in a total of 757 configurations

Table 1: ITU HF Channel Conditions from [14]

Channel Condition	Delay Spread (ms)	Doppler Spread (Hz)
Low Latitude, Quiet (LQ)	0.5	0.5
Low Latitude, Moderate (LM)	2	1.5
Mid Latitude, Quiet (MQ)	0.5	0.1
Mid Latitude, Moderate (MM)	1	0.5
Mid Latitude, Disturbed (MD)	2	1
High Latitude, Quiet (HQ)	1	0.5

for the ϵ-greedy CE to explore/exploit, with ϵ set to 0.3. The fixed LMS-DFE was set to have 15 feedforward taps, 10 feedback taps, and a step size of 0.001. The probabilities of error obtained for each SNR were averaged over 1000 independent trials (i.e. sending a training and testing sequence). The training sequence consisted of 500 symbols, and the testing sequence consisted of 2000 symbols.

Figures 3 - 8 show the results of our simulations for all of the channel conditions displayed in table 1. The figures indicate that the ϵ-greedy CE outperforms the preset LMS-DFE in each of the channel models. This is primarily due to its ability to characterize/select the tap-lengths and step sizes that provide fewer errors, while the preset LMS-DFE is unable to adapt. Figures 6 and 8 show that the error probabilities for both equalizers are slightly higher than the other scenarios, which may be due to the larger degradation of the channels as indicated by their respective delay and frequency spreads in table 1. This indicates the need for more robust equalizer algorithms to be utilized (i.e. turbo, frequency-domain, etc.) However, the ϵ-greedy CE is still able to provide a smaller amount of error overall.

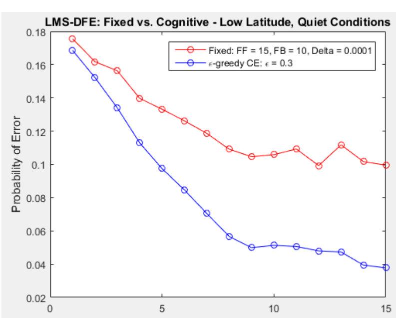

Figure 3: Probability of Error for LQ Channel

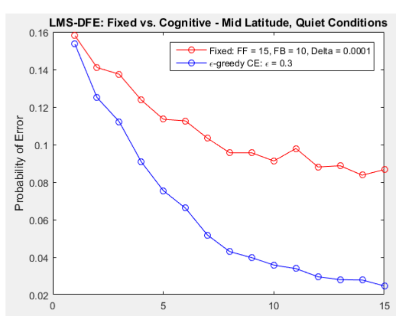

Figure 4: Probability of Error for MQ Channel

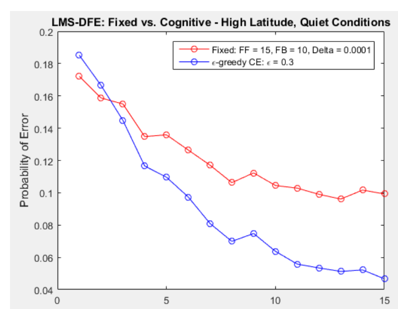

Figure 5: Probability of Error for HQ Channel

CONCLUSIONS

In this paper, we have introduced the concept of cognitive equalization as a means of maintaining reliable communications in the HF band. As stated earlier, being able to adjust the parameters of

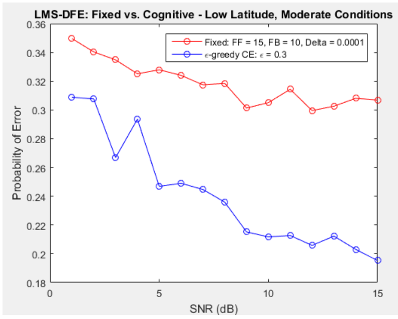

Figure 6: Probability of Error for LM Channel

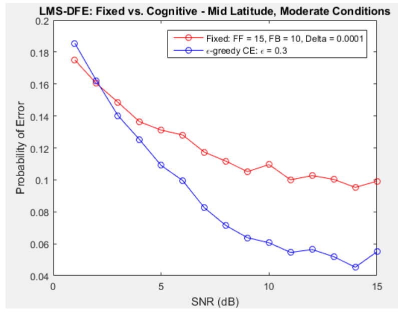

Figure 7: Probability of Error for MM Channel

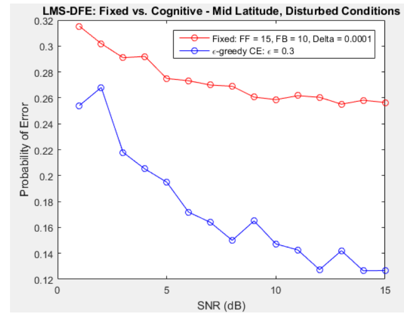

Figure 8: Probability of Error for MD Channel

an equalizer is critical, especially if channels share similar characteristics as the ionosphere, which exhibits frequent variations. We've used an ϵ-greedy CE to adjust the parameters of an LMS-DFE so that it can alter its structure with the objective of minimizing the probability of error. We have verified that under multiple, distinct HF environments, our cognitive equalization technique is able to provide a better performance than a fixed equalizer. One future direction we will investigate is expanding the concept of cognitive equalization by varying the learning algorithm used by the equalizer and the actual equalizer model itself (i.e. DFE, frequency-domain, decision-directed, turbo, etc.), as well as the tap length and step size. We will also use different CE algorithms, including meta-CEs [17], to observe if any performance improvements can be obtained. In additon, we will work towards verifying the effectiveness of cognitive equalization via long-range, over the air experiments.

ACKNOWLEDGEMENTS

This project was partially supported by the Broadband Wireless Access and Applications Center (BWAC); NSF Award No. 1265960.

REFERENCES

[1] N. Teku, G. Gulati, H. Asadi, G. Vanhoy, A. H. Abdelrahman, K. Morris, T. Bose, and H. Xin, "Design of a long range cognitive hf radio with a tuned compact antenna," *International Telemetering Conference 2017*, pp. 1–10, 2017.

[2] A. L. Saverino, A. Capria, and F. Berizzi, "Realization of a flexible technological demonstrator for hf sky-wave data links," *Progress in Electromagnetics Research Symposium Proceedings*, pp. 2305–2309, 2015.

[3] M. Uysal and M. R. Heidarpour, "Cooperative communication techniques for future-generation hf radios," *IEEE Communications Magazine*, vol. 50, pp. 56–63, October 2012.

[4] A. D. Sabata and C. Balint, "Structure of signal received by passive ionospheric sounding in the hf band at the location of timisoara, romania," in *2016 12th IEEE International Symposium on Electronics and Telecommunications (ISETC)*, pp. 55–58, Oct 2016.

[5] T. Vanninen, T. Linden, M. Raustia, and H. Saarnisaari, "Cognitive hf; new perspectives to use the high frequency band," in *2014 9th International Conference on Cognitive Radio Oriented Wireless Networks and Communications (CROWNCOM)*, pp. 108–113, June 2014.

[6] H. Asadi, H. Volos, M. M. Marefat, and T. Bose, "On Quantifying the Experience Level of a Cognitive Engine," *SDR-WInnComm*, pp. 9–15, 2015.

[7] J. Proakis, M. Salehi, and G. Bauch, *Contemporary Communication Systems Using MATLAB*. Cengage Learning, 2012.

[8] D. Brilyantarto, I. Kurniawati, and G. Hendrantoro, "Early results on the design of adaptive equalizer for hf communications system on equatorial region," in *2014 XXXIth URSI General Assembly and Scientific Symposium (URSI GASS)*, pp. 1–4, Aug 2014.

[9] R. J. Tront, "Performance of Kalman Decision-Feedback Equalization in HF Radio Modems," Master's thesis, University of British Colombia, 1984.

[10] S. Haykin, *Adaptive Filter Theory*. Pearson, 2014.

[11] H. I. Volos and R. M. Buehrer, "On balancing exploration vs. exploitation in a cognitive engine for multi-antenna systems," in *GLOBECOM 2009 - 2009 IEEE Global Telecommunications Conference*, pp. 1–6, Nov 2009.

[12] J. White, *Bandit Algorithms for Website Optimization: Developing, Deploying, and Debugging*. O'Reilly Media, 2012.

[13] C. Watterson, J. Juroshek, and W. Bensema, "Experimental confirmation of an hf channel model," *IEEE Transactions on Communication Technology*, vol. 18, pp. 792–803, December 1970.

[14] I.-R. F.1487, "Testing of HF modems with bandwidths of up to about 12 kHz using ionospheric channel simulators," *ITU*, vol. 1487, 2000.

[15] R. Otnes, *Improved Receivers for Digital High Frequency Communications: Iterative Channel Estimation, Equalization, and Decoding (Adaptive Turbo Equalization)*. PhD thesis, 2003.

[16] E. Johnson, E. Koski, and W. Furman, *Third-generation and Wideband HF Radio Communications*. Artech House mobile communications series, Artech House, 2013.

[17] H. Asadi, H. Volos, M. M. Marefat, and T. Bose, "Metacognition and the next generation of cognitive radio engines," *IEEE Communications Magazine*, vol. 54, pp. 76–82, January 2016.