ENEL 671 Adpative Signal Processing Project Report

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***Abstract*—The purpose of this project is to analyze the performance of three different adaptive algorithms. These algorithms, which can be used for a variety of applications such as echo cancellation and multipath mitigation, are implmented for the purposes of equalizing a dispersive channel. The first algorithm investigated is the Least Mean Squares (LMS). The LMS filter uses a search method to minimize the mean square error. The performance of the LMS is then compared to the Recursive Least Squares (RLS) method, which minimizes a weighted linear least squares cost funtion. Finally the Recursive Least Squares Lattice algorithm is implemented in the third project for joint process estimation. The algorithms are tested against multiple channels with varying eigenvalue spreads. Furthermore different design parameters such as step size and filter order are evaluated. The performance with regards to convergence speed and complexity is discussed. The RLSL appears to have performance advantages in terms of convergence speed at the cost of significant increase in complexity.**

I. Introduction

ADAPTIVE filtering is used for a variety of applications. When communicating across a dispersive channel, a signal is destorted by effects of multipath, noise etc REFERENCE. To recover the correct message at the receiver, an adaptive filter is implemented to equalize the channel. In general, an algorithm is used to calculate the optimum filter coefficients to minimize the error between transmit and receive. In practice, a signal transmitted along a channel contains a preamble, which is a known sequence of data that is used to esimate the parameters of the channel. The statistics are assumed to be stationary in the window of time that each preamble is sent.

The most common adaptive equalizers involve the LMS, RLS, ans RLSL algorithms. The performance of these methods varies and they each have their advantages and disadvantages. The LMS is relatively simplistic in terms of implmentation. However, it's drawback is that it uses a stochastic search gradient and which limits its ability to find an optimum solution, is inefficient and not practically capable of removing all distortions. The RLS algorithm is typically an order of magnitude faster because it whitens the input data gy using the inverse correlation matrix of the data, assumed to be of zero mean REF. The RLSL algorithm uses a lattice predictor along with a stage that estimates the error of the next filter order at each time step.

The methodology used for designing of the filters in this project will be discussed. Afterwards a detailed analysis of the results for each project and a summary of their implications will be discussed. Finally a conclusions section will highlight the general results drawn from each experiment.

II. Equalization Methodology

ADAPTIVE equalization is designed to remove unwanted signals from a channel output which can be caused by multipath or other distortions. In Figure 1 the general block diargram that is simulated in these experiments is outlined. A data source that generates a random BPSK signal goes through a dispersive channel that has three paths and white noise. The adaptive filter reduces the effects of these signal distortions to generate the output.To compare the output of the filter to the truth data source adequate delay must be added to the BPSK data. The optimal delay is given by half the filter order, that is:

$$\Delta = \frac{M}{2}$$

The output of each stage is as follows:

$$\boldsymbol{u}(n) = \begin{bmatrix} u(n) & u(n-1) & ... & u(n-M+1) \end{bmatrix}^T$$

$$= \boldsymbol{h}^T(n)\boldsymbol{a}(n) + \boldsymbol{v}(n)$$

$$\boldsymbol{w} = \begin{bmatrix} w_0 & w_1 & ... & w_{M-1} \end{bmatrix}^T$$

$$= \boldsymbol{w}(n-1) + \mu\boldsymbol{u}(n)e(n)$$

$$\hat{d}(n) = y(n) = \boldsymbol{w}^T(n)\boldsymbol{u}(n) = \boldsymbol{u}^T(n)\boldsymbol{w}(n)$$

$$e(n) = d(n) - \hat{d}(n) = d(n) - \boldsymbol{w}^T\boldsymbol{u}(n)$$

$$a(n) = d(n) - \hat{d}(n) = d(n) - \boldsymbol{w}^T\boldsymbol{u}(n)$$

$$\boldsymbol{R} = E[\boldsymbol{u}(n)\boldsymbol{u}(n)^T]$$

$$\boldsymbol{p} = E[\boldsymbol{u}(n)d(n)]$$

$$\boldsymbol{J}(n) = \sigma_d^2 - 2\boldsymbol{w}^T\boldsymbol{p} + \boldsymbol{w}^T\boldsymbol{R}\boldsymbol{w}$$

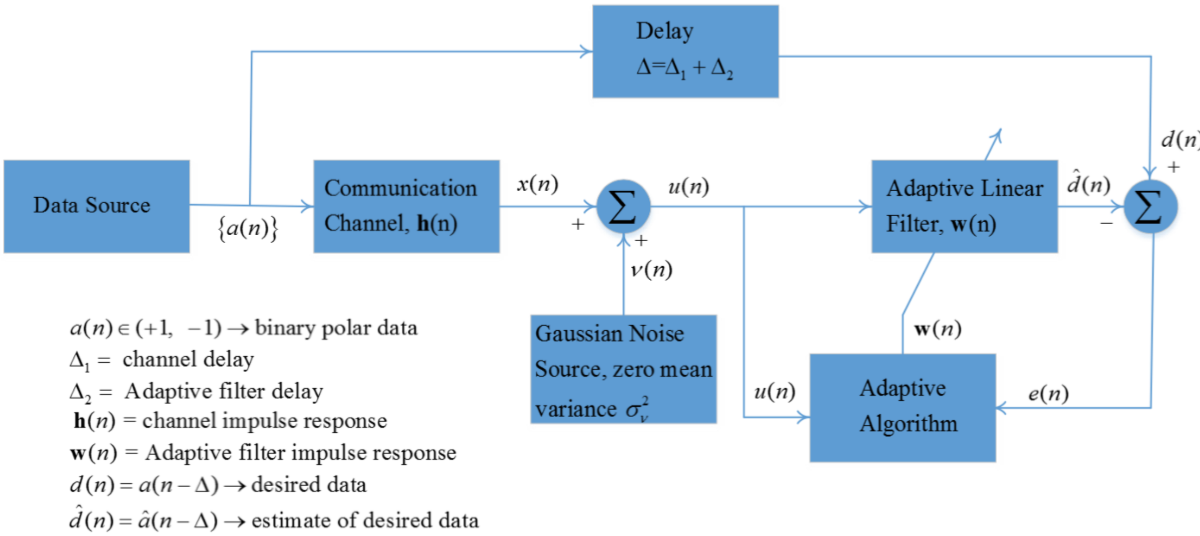

Fig. 1: Block Diagram for Equalization

III. Pre Experiment Calculations

IV. Project 1: Least Mean Squares Algorithm

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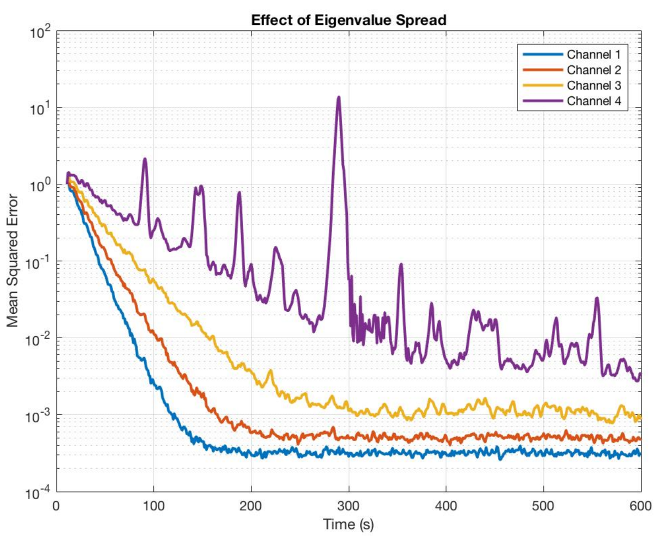

Fig. 2: BLAH BLAH

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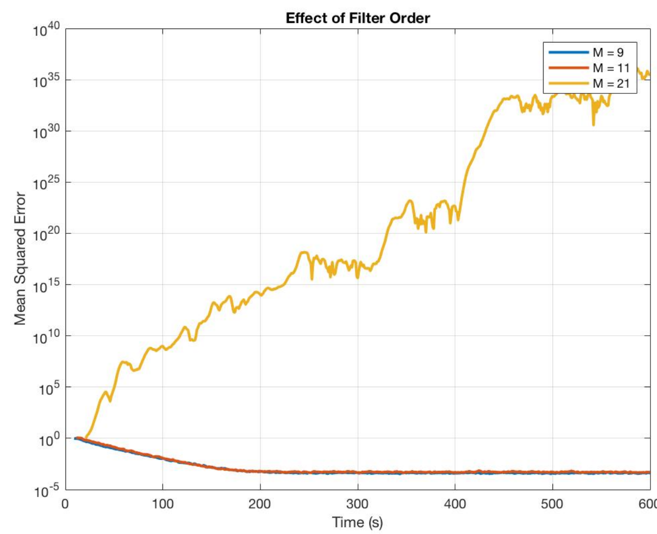

Fig. 3: BLAH BLAH

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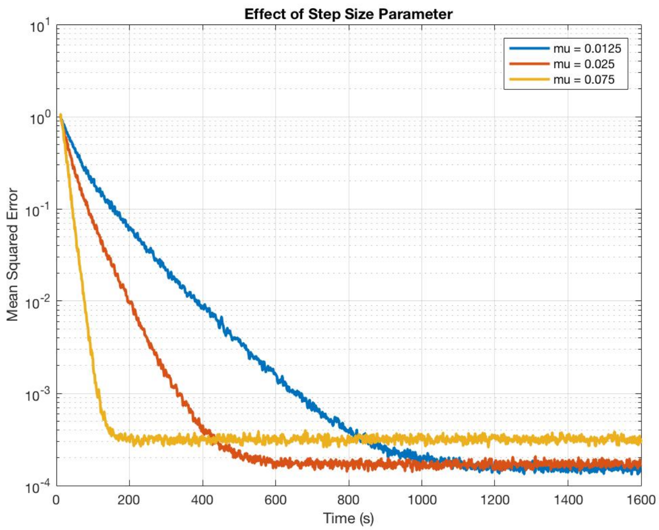

Fig. 4: BLAH BLAH

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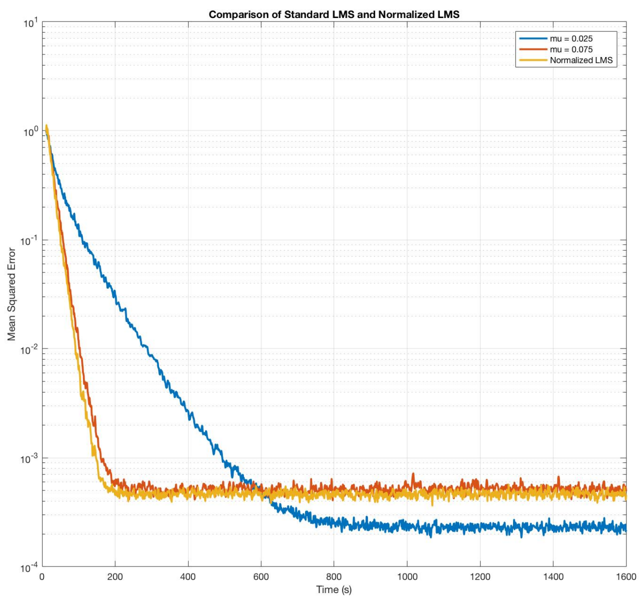

Fig. 5: BLAH BLAH

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V. Conclusion

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Appendix A
Proof of the First Zonklar Equation

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Appendix B

Appendix two text goes here.

Acknowledgment

The authors would like to thank...

References

[1] H. Kopka and P. W. Daly, *A Guide to LaTeX*, 3rd ed. Harlow, England: Addison-Wesley, 1999.

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Michael Shell Biography text here.

John Doe Biography text here.

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