EE 594 - Adaptive Signal Processing

Fall 2002 – Exam #2

This is a take-home examination due at the beginning of class on Wednesday, November 13, 2002.

“The attached solution is due entirely to my own, individual efforts. In no way have I consulted with anyone other than (possibly) the instructor of this course in creating these solutions.”

Signature: ____ Date: _________

Print: ____

Problem 1	/ 25 points
Problem 2	/ 25 points
Problem 3	/ 25 points
Problem 4	/ 25 points
Total	/ 100 points

Problem 1

Recreate Haykin, p. 475, Fig. 10.10c. Comment.

Problem 2

The adaptive line enhancer (ALE) is a device that may be used to detect a periodic signal buried in a broad-band noise background. Complete details about the ALE are given in Haykin, Section 9.3, Example 5. The basic system is illustrated in Fig. P2 below.

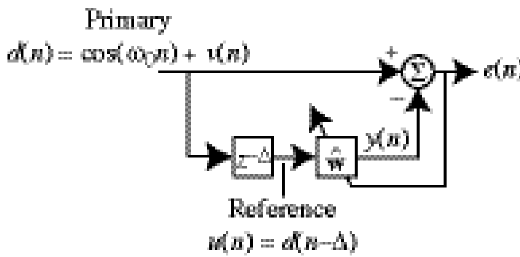

Figure P2: Adaptive Line Enhancer

Let $v(n)$ be a zero mean, unit variance white gaussian; $\omega_0 = \pi / 4$; and $M = 10$.

(a) Justify choosing $\Delta = 1$.

(b) Compare the performance of NLMS and GNLMS ($P = M$) in this application. Plot learning curves for at least 100 simulations making sure misadjustment is calibrated. Comment.

(c) Download the following MATLAB data file (zipped for convenience)

`http://www.ece.nmsu.edu/~pdeleon/Teaching/EE594/Exam2.zip`

which contains $d(n)$ and f_s. Using NLMS specify your choice of M and Δ and plot the MSE (MA filtered for readability). You will be graded on the overall learning curve. Note that you must initialize the adaptive filter to the null vector and are allowed only one run.

(d) Listen to $d(n)$ and $e(n)$. Carefully describe what you hear.

Problem 3

In this problem we wish to verify the claim that RLS converges in approximately $2M$ iterations where M is the filter length. Simulate the system modeling configuration illustrated in Fig. P3 where $u(n)$ is zero mean, unit variance, white Gaussian noise; the unknown system is given by

$$H(z) = \frac{1}{1 - 0.5z^{-1}};$$

$x(n)$ is zero mean, 10^{-4} variance, white Gaussian noise [uncorrelated to $u(n)$]; and $\xi(n)$ is the *a priori* error (used in plotting RLS learning curves). Assume $\lambda = 1$ (infinite memory) and start adaptation at $n = M$ so that startup transient does not impact performance.

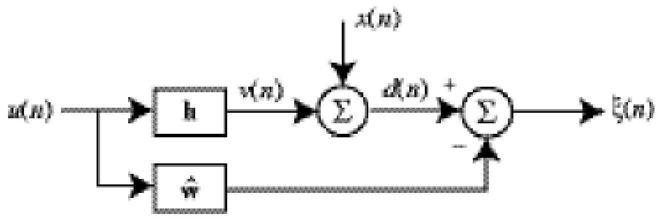

Figure P3: System modeling configuration.

(a) Why would we include the additive noise, $x(n)$ in simulations? What does it represent? If you are not sure, examine what happens when you do not include it.

(b) On a single figure, plot the learning curve for M = 5, 10

(c) On a single figure, plot the learning curve for M = 50, 100.

(d) Fill in the table

M	Convergence Time (samples)
5	
10	
50	
100	

(e) Based on your results, comment on the claim of RLS convergence speed.

Problem 4

In this problem we wish to verify the theoretical results regarding misalignment variance of the RLS algorithm. For simulations, use the familiar adaptive equalizer of Section 13.7 with $W = 2.9$ and $\sigma^2 = 0.001$. Be sure to start adaptation at $n = M$.

(a) Plot the eigenvalues of **R** (sorted from highest to lowest).

(b) On a single figure, plot in units of dB,

(i) Experimental misalignment variance (100 simulations and $\lambda = 1$), $E[\varepsilon^H(n)\varepsilon(n)]$ where $\varepsilon(n) = \mathbf{w}_{opt} - \hat{\mathbf{w}}(n)$

(ii) Theoretical misalignment variance

$$E[\varepsilon^H(n)\varepsilon(n)] = \frac{\sigma^2}{n - M - 1}\sum_{k=1}^{M}\frac{1}{\lambda_k} \qquad , n > M + 1$$

(c) Comment on your results with the RLS misalignment variance.

(d) For $\lambda = 0.1, 0.5, 0.9$ plot the learning curves and verify the theoretical result for RLS misadjustment, given by

$$\text{Misadjustment} = M\left(\frac{1-\lambda}{1+\lambda}\right).$$

Remember that for $\lambda = 1$, there is zero misadjustment.