

ADAPTIVE EQUALISERS IN SMART ANTENNA

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ABSTRACT

This paper presents work done within the frame work of smart antenna systems. Smart antenna systems have gained increased interest as they promise to provide significant increase in system capacity and performance and greater coverage, meaning less base stations are needed to cover the same area compared to conventional antennas. Since greater demands for fast data transmission rates leads to greater inter-symbol interference (ISI) in the received data, due to multipath propagation. Adaptive equalisers can be used periodically to estimate the communication channel ($1/H$) and then performing equalisation (inverse modelling) to reduced the effect of ISI. To this end, Least mean Square (LMS) adaptive algorithm is chosen for its computational simplicity and high stability. Using the standard and Detection Guided LMS algorithms, previous adaptive equalisations studies have modelled the communication channel as a Finite Impulse Response (FIR) filter (Shannon L, 2002). This paper will model the communication channel as an Infinite Impulse Response (IIR) filter to show that FIR system findings do hold for the IIR systems.

KEYWORDS: *Inter-symbol interference (ISI), Least mean Square (LMS), Finite impulse Response (FIR), Infinite Impulse Response (IIR), communication channel ($1/H$).*

INTRODUCTION

In most mobile channels, there are more than one propagation path between transmitter and receiver, and a received signal consists of two or more components, each of which travelled a different path from the transmitter. Each multipath component arrives with a delay depending on the path length. Delayed multipath components can cause inter-symbol interference (ISI) and impose an upper data rate that the channel can support without the use of an expensive equaliser (Shannon L, 2002). However, previous adaptive equalisation studies have modelled the unknown communication channel as a finite Impulse Response (FIR) filter and the adaptive equaliser as an Infinite Impulse Response (IIR) filter.

METHODOLOGY

In this paper standard and Detection Guided Least mean square (LMS) algorithm will be used to model the unknown communication channel as an Infinite Impulse response (IIR) filter and therefore the adaptive equaliser as a FIR filter. The advantage of this representation is that a FIR equaliser provides a better stability over an IIR equaliser. These investigations are simulated using MATLAB.

Adaptive Equalisation

An Adaptive equalisation involves periodically training the equaliser to enable it to adapt itself to any changes in communication channel.

Overview of LMS Adaptive FIR filter

The proposed LMS adaptive FIR filter consists of two processes. The first is a filtering process that involves computing the output of the FIR filter, produced by a set of tap inputs, and also generating an error estimate by comparing the output to a known desired response. The second is an adaptive process involving the automatic adjustment of the tap weight of the filter according to the error estimation computed in the first process. These two processes combine to form a feedback loop around the LMS algorithm described (Haykin S, 1996). The block diagram of the proposed equaliser is shown in figure 1, where at sample instant k , the input signal is $u(k)$, the interference signal is represented by $n(k)$ and $r(k)$ is the output signal from an unknown channel $1/H$, which is added with the $n(k)$ to form the received signal $y(k)$. The signal $y(k)$ is then passed through the equaliser F , to give the signal $x(k)$. Finally, $x(k)$ is compared with the original transmitted signal $u(k)$, to give the error signal $e(k)$, the role of the equaliser is to resolve the distortion of the channel by minimising the effect of additive noise at its output (Beigy, 2001).

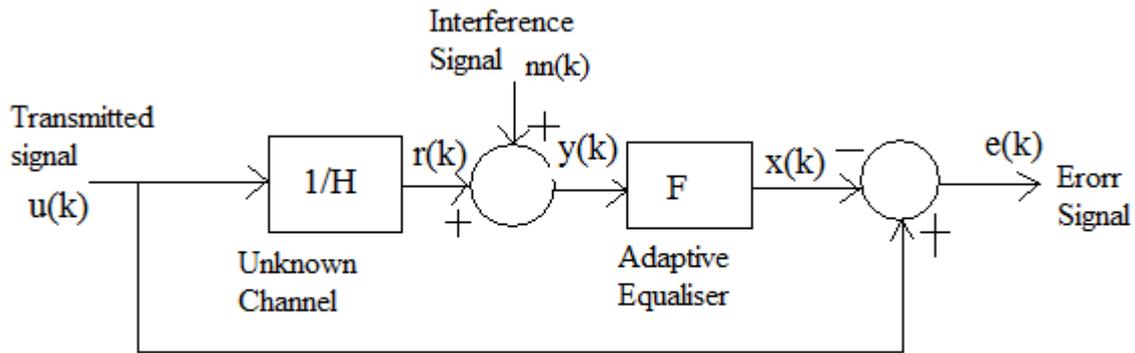


Figure 1: Block Diagram of adaptive equalisation system

Channel Equaliser Impulse Response Model

A. General Impulse response model representation

Reference to figure 1 while reading the following assumptions, we can assume that the unknown channel $1/H$ is linear, time invariant and able to be modelled as a discrete-time IIR filter with n taps.

$$H = [h_0, h_1, h_2, \dots, h_{n-1}] \quad (1)$$

The time invariant, n -tuple, IIR modelled, unknown channel with only $m \ll n$ non-zero (active) taps and $h_0 = 1$

The LMS adaptive FIR filter (Equaliser) has a tap delay line structure and a length of n .

$$F(k) = [f_0, f_1, f_2, \dots, f_{n-1}] \quad (2)$$

The tap coefficient of $F(k)$ are initially set to zero

$$F_i(0) = 0 \text{ for } i = 0, 1, 2, \dots, n-1 \quad (3)$$

In order to calculate the output $r(k)$ from the unknown channel $1/H$, the system requires knowledge of the last $n-1$ values of r .

$$R(k) = [r(k-1), r(k-2), r(k-3), \dots, r(k-n+1)] \quad (4)$$

Is used to calculate the output as

$$r(k) = \frac{1}{(H(1))(u(k) - H(2:n)R^T(k))} \quad (5)$$

where $H(1) = h_0$ and $H(2:n) = [h_1, h_2, \dots, h_{n-1}]$

The output signal then has the interference signal $nn(k)$ added to it to produced the received signal

$$y(k) = r(k) + nn(k) \quad (6)$$

The received signal $y(k)$ is then added to an array of the last $n-1$ received signal to form the received signal vector

$$Y(k) = [y(k), y(k-1), y(k-2), \dots, y(k-n+1)] \quad (7)$$

This vector is then input into the adaptive equaliser F to produced the estimate $x(k)$ of the transmitted signal

$$x(k) = F(k-1)Y^T(k) \quad (8)$$

The estimate $x(k)$ is compared to the original transmitted signal $u(k)$ to produced an error signal:

$$e(k) = u(k) - x(k) \quad (9)$$

Ideally, the error signal $e(k)$ should be equal to the interference signal $nn(k)$. This would indicate that LMS adaptive equaliser has successfully estimate H . It can be shown that tap weights of the equaliser F are functions of the sampling instant k . The LMS algorithm adjust the tap weights, of coefficients of the FIR equaliser in an attempt to minimise the mean squared error (MSE) $e^2(k)$.

However instantaneous error $e(k)$ is used to estimate the gradient of the MSE surface (Haykin S, 1996).

Eventually, the standard LMS equation of FIR equaliser is given by:

$$F(k) = F(k-1) + \mu Y(k)e(k) \quad (10)$$

Where $y(k)$ is the received signal vector from (7) and μ is the step-size parameter.

B. Stability of the LMS Algorithm

A crucial parameter affecting the stability and convergence rate of the LMS algorithm is the value of the step-size parameter μ . The larger the value of μ , the faster the convergence and hence the higher the stability of LMS adaptive equaliser (Hermer J 2000). In (Being G.L,2001),(How, L. 2001) the value of μ is said to usually be chosen within the range:

$$0 < \mu < \frac{2}{\sum_{i=k-n+1}^k \mu^2(i)} \quad (11)$$

C. Detection Guided LMS

Homer et al proposed an active tap detection scheme with the aim of detecting the active taps and subsequently LMS estimating these taps (Hermer J 2000). By reducing the number of taps being estimated, faster convergence and accuracy occurs. Other researchers before them had proposed active tap threshold based on intuition whereas the theoretical solutions proposed in (Hermer J 2000) focuses on the minimisation of the least square cost function.

The formula for the tap activity measure is derived as in (Being G.L,2001),(Hermer J 2000):

$$X_j(k) = \frac{[\sum_{i=j+1}^k [(u(k)y(k-i) - \hat{x}(k)y(k-i) + F_j(k-i)y^2(k-i))] 2]}{\sum_{i=j+1}^k y^2(k-i)} \quad (12)$$

Where j is the tap number of the equaliser, k is the sampling instant and $F_j(k-i)$ the estimate of h_j at instant $k-1$. This approach requires prior knowledge of the known channel in order to choose a correct value of m . Where m is the most active taps. A prior choice of m would lead to either the inclusion of active taps or the exclusion of some active taps from the group of taps being estimate (Homer J, Mareals I, 1998). A better method is to detect the taps that are active, rather than m most active taps. The formula for the activity threshold when modelling the unknown channel as an IIR filter is :

$$T(k) = \frac{\log_2(k)}{k} \sum_{i=1}^k \mu^2(i) \quad (13)$$

Where k is the sampling instant and K is deemed active if

$$X_j(k) > T(k) \quad (14)$$

Each tap in the adaptive filter F is tested using (14) at each sample interval k . The tap activity variable $g(j)$ is set to 1 or 0 if the tap is inactive. Using the following equation, only taps that are calculated for being active will be adapted.

$$F_j(k) = g(j)F_j(k-1) + g(j)\mu y(k-j+1)e(k) \quad (15)$$

SIMULATION RESULTS

All LMS equalisation simulations are assumed to have a time invariant unknown communication channel $1/H$, with input signal $u(k)$ and interference signal $nn(k)$ having variances $\sigma_u^2 = 1$ and $\sigma_{nn}^2 = 0.1$ the interference signal $nn(k)$ is assumed to be white zero mean Gaussian signal. The number of samples interval N is set at 5000 and the fixed value of μ at 0.008. The unknown channel $1/H$, was set according to H having length $n=25$. Of these 25 taps, only 5 tap are nonzero being $h_1 = 1, h_5 = 0.6, h_{10} = 0.36, h_{15} = 0.216$ and $h_{20} = 0.1296$.

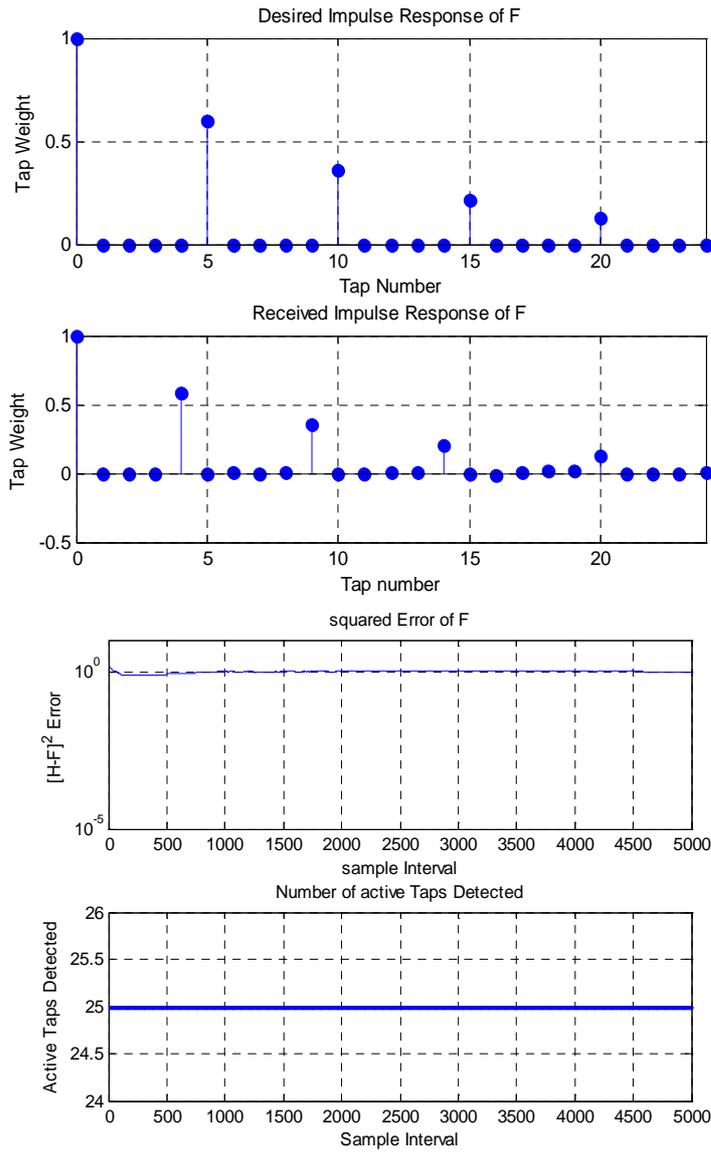
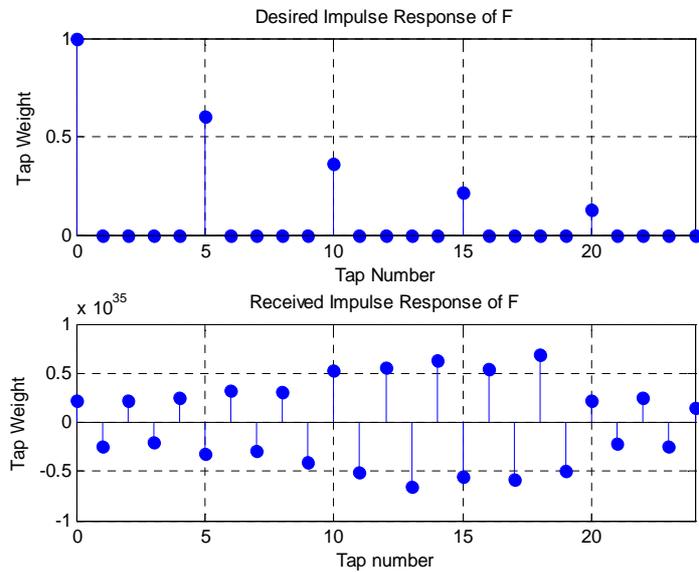


Figure 2: standard LMS equaliser with White Input



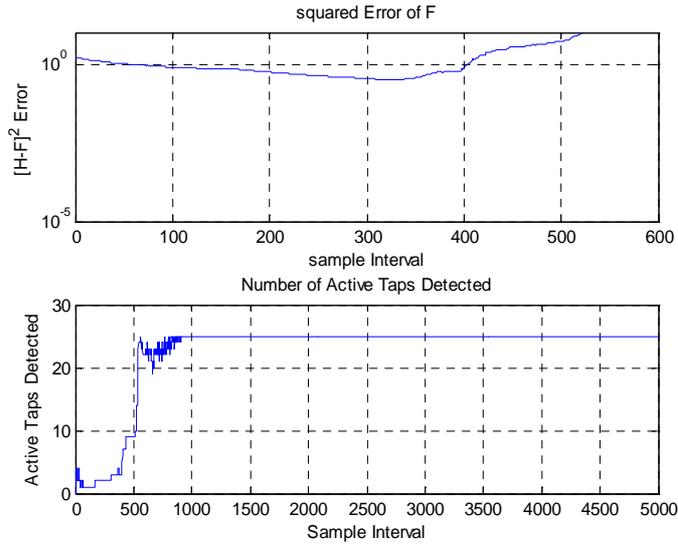


Figure 3: Detected Guided LMS equaliser with White Input

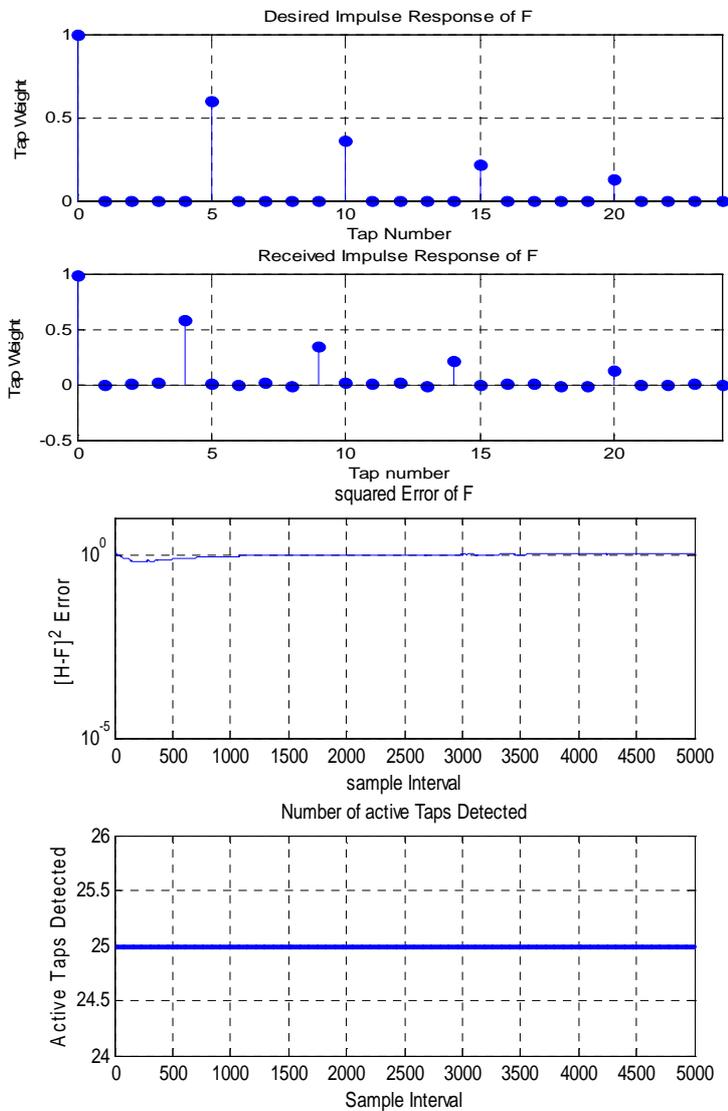


Figure 4: Standard LMS equaliser with colour Input

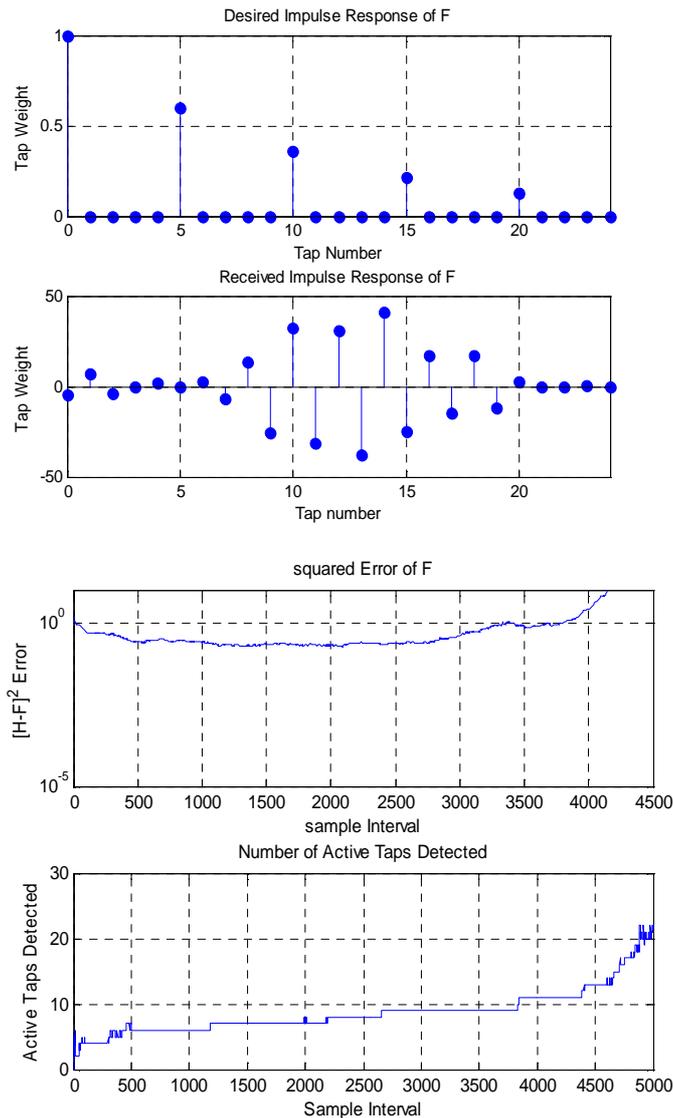


Figure 5: Detected Guided LMS equaliser with colour Input

Table 1: Summary of the simulated results

	Standard with input	LMS white	Detected Guided LMS with coloured input	Standard LMS with coloured input	Detected Guided LMS with coloured input
Mean squared error	1.006		0.7753	0.8707	0.2804
Sample interval of 0.001	1000		1000	1000	1000
Active taps Detected	25		6	25	6

CONCLUSIONS

A summary of LMS equalisation results can be found in table 1. The table displayed the approximation mean values for the squared error of F after convergence;

It can be seen clearly from the table that both Detected Guided Schemes for white and coloured inputs provide better channel equalisation, as

their squared error values are much lower compared to the standard versions of the LMS algorithm. Both Detection Guided schemes are also able to correctly detect six active taps whereas the standard schemes incorrectly detected all 25 taps as being active. These results are consistent with the findings in (Being G.L, 2001) as expected.

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