On the various LMS Algorithms for FS-DFE with Low Hardware Complexity suitable for the High Order QAM Application


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ABSTRACT

In this paper, the performance and convergence time comparisons of various LMS algorithms that is used for coefficient update of channel equalizer and adaptive filter, are presented. We choose the optimum LMS algorithm suitable for the low complexity, high performance and high order QAM applications. The presented Fractionally Spaced Decision Feedback Equalizer accommodates 64 and 256QAM formats, and incorporates T/2-spaced feed-forward filter(FFF), feedback filter(FBF), a carrier recovery loop and an error monitor. The FFF and FBF have both16-tap filters based on various LMS(LMS, data signed LMS, error signed LMS, signed signed LMS) coefficient updating algorithms. To achieve area efficiency, time-multiplexed multiplication and tap-sharing techniques are employed. We simulated the design using SPW™ in AWGN channel and also severe multipath channel.

1. INTRODUCTION

A digital communications receiver not only has to contend with ISI. but also has to acquire proper carrier and timing synchronization with the transmitter. Some methods for joint blind equalization and synchronization have been proposed[1][2]. In this paper, we are only concerned with joint equalization and carrier recovery.

Common equalizers have two modes of operations. one is a training mode and the other is a decision-directed mode. In the training mode the transmitter sends a training sequence known to the receiver and the equalizer adapts its coefficients utilizing the received signal and the known training sequence. When the coefficients are converged, the equalizer switches to the decision-directed mode, which treats the decision circuit output as the correct transmitted data, for continued adaptation and tracking of channel variation. However, in some situations it may be costly to send a training sequence and the training sequence may be unavailable at the receiver. In these cases, blind training is needed, n which we make use of some known statistics of the transmitted data, but not the exact data values, to adapt the equalizer coefficients. Sato's and Godard's techniques[3] are perhaps the most referenced blind training (or blind equalization) methods. The Blind Decision Feedback Equalizer for cable modem will accommodate 64 and 256QAM formats, and will incorporate a 16-tap feedforward equalizer (FFE), a 16-tap feedback equalizer (FBE), a carrier recovery loop, and an error monitor.

Least Mean Square (LMS) algorithm is an important member of the family of stochastic gradient algorithms. The term "stochastic gradient" is intended to distinguish the LMS algorithm from the method of steepest descent that uses a deterministic gradient in a recursive computation of the Wiener filter for stochastic inputs. A significant feature of the LMS algorithm is its simplicity. Moreover, it does not require measurements of the pertinent correlation functions, nor does it require matrix inversion. Indeed, it is the simplicity of the LMS algorithm that has made it the standard against which other adaptive filtering algorithms are benchmarked.[4]

This paper presents the performance and convergence time comparisons among the LMS, signed LMS(about input data and error), signed signed LMS coefficient update algorithms in Fractionally Spaced DFE for Cable Modem. This paper is organized as follows. Section 2 provides a blind decision feedback equalizer architecture. Section 3 shows simulation results of the performance and convergence time of T/2-spaced DFE using LMS, Signed LMS, Signed-Signed LMS tap adaptation algorithms in AWGN and severe multipath channels. and describe of the result. Finally, the conclusions are given in Section 4.

2. ARCHITECTURE OF DFE

Fractionally Spaced Decision Feedback Equalizer consists of a feedforward section and a feedback section, coefficient adaptation block and error function block [4]. Fig.1 shows the block diagram of modified decision feedback equalizer. While feedforward filter section applies the input signal received to equalize, feedback adaptive FIR section receives the decision
value of the previously detected equalizer output. Thus, DFE could induce the error propagation. However, this phenomenon is less significant than performance enhancement by subtracting out the portion of ISI produced by previously detected symbols from the estimates of future symbols [4].

A. Channel

The equalizer is simulated in AWGN channel and given in the severe multipath channel based on MCNS specifications[4]. The channel environments for simulation in this paper are summarized in Table 1. We chose the optimum tap length of FFE, DFE and the step size $\mu$ of CMA, decision directed algorithm (DDA) for AWGN and this channel.

<table>
<thead>
<tr>
<th>Impairment</th>
<th>64 QAM</th>
<th>256 QAM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Symbol Rate</td>
<td>5.056941 MHz</td>
<td>5.360537 MHz</td>
</tr>
<tr>
<td>Roll-off Factor</td>
<td>0.18</td>
<td>0.12</td>
</tr>
<tr>
<td>Frequency Offset</td>
<td>$\pm 0.07/T$</td>
<td>$\pm 0.05/T$</td>
</tr>
<tr>
<td>Input Noise SNR</td>
<td>23.5 dB</td>
<td>30.0 dB</td>
</tr>
<tr>
<td>Multipath</td>
<td>$-5$ dB @ $\leq 500$ nsec</td>
<td>$-5$ dB @ $\leq 500$ nsec</td>
</tr>
<tr>
<td></td>
<td>$-10$ dB @ $\leq 1000$ nsec</td>
<td>$-10$ dB @ $\leq 1000$ nsec</td>
</tr>
<tr>
<td></td>
<td>$-15$ dB @ $\leq 1500$ nsec</td>
<td>$-15$ dB @ $\leq 1500$ nsec</td>
</tr>
<tr>
<td></td>
<td>$-25$ dB @ $&gt; 1500$ nsec</td>
<td>$-25$ dB @ $&gt; 1500$ nsec</td>
</tr>
</tbody>
</table>

Table 1 Summarization of Channel Environment

B. FFF and FBF Architecture

The complex equalizer consists of two 16-tap transposed form adaptive FIR filters for feedforward filter(FFF) and feedback filter (FBF). Each filter employs a parallel-tap architecture which allows simple control distribution and data propagation, plus convenient scalability for applications requiring different equalizer spans. The FFF has fractionally spaced (T/2-spaced) structure. The fractionally spaced equalizer is implemented as a decimated-by-2 structure while output samples are produced at the symbol rate. Fig2 shows the basic transpose-form T/2 spaced FFE. All registers except the last one are triggered by a clock with twice the symbol rate (2fs, where fs=1/Ts). The last register is triggered at each n times (n is integer) and discards every other output sample at 2(n - 1)Ts/2. This structure is straight-forward but almost all circuitry including the multiply-add elements have to operate at twice the symbol rate[7].

C. Types of LMS Coefficient Update

The general form of an adaptive FIR filtering algorithm is $c_i(n+1)=c_i(n)+\mu \cdot \Phi(n) \cdot x^*(n)$, where $\Phi(n)$ is a particular vector-valued nonlinear function, $\mu(n)$ is a step size parameter, $c(n)$ and $x(n)$ are the error signal and input signal vector, respectively, and $\Phi(n)$ is a vector of states that store pertinent information about the characteristics of the input and error signals and/or the coefficients at previous state of time n.

The step size is so called because it determines the magnitude of the change or "step" that is taken by the algorithm in iteratively determining a useful coefficient vector. Often, success or failure of an adaptive filtering application depends on how the value of $\mu(n)$ is chosen or calculated to obtain the best performance from the adaptive filter. By restriction the step size $\mu(n)$ to be a power-of-two, the hardware implementation of coefficient adaptation block is simplified.

a. LMS coefficient update [5]

$$c_i(n+1) = c_i(n) + \mu \cdot \Phi(n) \cdot x^*(n) \quad k = 1,...,16 \quad (1)$$

b. Input Data Signed LMS coefficient update

$$c_i(n+1) = c_i(n) + \mu \cdot \Phi(n) \cdot \text{sgn}[x^*(n)] \quad k = 1,...,16 \quad (2)$$

where,

$$\text{sgn}(x^*) = 1 \quad \text{if } x^* > 0$$
$$\text{sgn}(x^*) = -1 \quad \text{if } x^* < 0$$

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where,

$$\text{sgn}(x^*) = 1 \quad \text{if } x^* > 0$$
$$\text{sgn}(x^*) = -1 \quad \text{if } x^* < 0$$

c. Error Signed LMS coefficient update

$$c_i(n+1) = c_i(n) + \mu \cdot \text{sgn}(e(n)) \cdot x^*(n) \quad k = 1,...,16 \quad (3)$$

where,

$$\text{sgn}(e) = 1 \quad \text{if } e > 0$$
$$\text{sgn}(e) = 0 \quad \text{if } e = 0$$
$$\text{sgn}(e) = -1 \quad \text{if } e < 0$$

d. Signed Signed LMS coefficient update

$$c_i(n+1) = c_i(n) + \mu \cdot \text{sgn}(e(n)) \cdot \text{sgn}[x^*(n)] \quad k = 1,...,16 \quad (4)$$

where,

$$\text{sgn}(x^*) = 1 \quad \text{if } x^* > 0$$
$$\text{sgn}(x^*) = -1 \quad \text{if } x^* < 0$$
$$\text{sgn}(e) = 1 \quad \text{if } e > 0$$
$$\text{sgn}(e) = 0 \quad \text{if } e = 0$$
$$\text{sgn}(e) = -1 \quad \text{if } e < 0$$

D. The Error Generation Function

For Constant Modulus Algorithm(CMA) Mode is as follows;

$$e(n) = y(n) \left[ R^2 - |y(n)|^2 \right] \cdot R^2 = \frac{E [ e(n) ]}{E [ |y(n)| ]} \quad (5)$$

The error generation function for Decision Directed Algorithm(DDA) Mode is as follows;

$$e(n) = D e c \left[ y(n) \right] \cdot y(n) \quad (6)$$

Fig.2 T/2-Spaced Feedforward Equalizer
E. Carrier Recovery Loop

The decision-directed carrier recovery cannot operate robustly under excessive decision errors. Hence the timing recovery and the FFF need be converged to a large extent before engaging of the carrier recovery. The frequency offset that CR Loop must compensate is 350KHz for 64QAM and 250KHz for 256QAM, while the frequency offset is reduced to about 20KHz using automatic frequency control(AFC) before carrier recovery loop. Thus carrier recovery loop is within 20KHz range. A second-order phase lock loop(PLL) is used to achieve the lock.

F. Error Monitor and CR Lock Detector

This block plays an important roles as an estimator. One is C<sub>e</sub>£Ò lock detector that has not only a very fast carrier acquisition time by adjusting the bandwidth of loop filter but also produce signal for reducing remaining phase error. Another is the switching from the blind mode to the decision directed mode by computing MSE at the decision device output.

![Block diagram of carrier recovery](image)

**Fig.3** Block diagram of carrier recovery

**3. SIMULATION RESULT**

![256QAM Data Signed LMS Algorithm : SNR 30dB](image)

**Fig.4** 256QAM Data Signed LMS Algorithm : SNR 30dB

![256QAM Error Signed LMS Algorithm : SNR 30dB](image)

**Fig.5** 256QAM Error Signed LMS Algorithm : SNR 30dB

![256QAM Signed Signed LMS Algorithm : SNR 30dB](image)

**Fig.6** 256QAM Signed Signed LMS Algorithm : SNR 30dB

Fig.4 - 6 show the characteristics of convergence by using various LMS algorithms in 256QAM mode. They display the constellation of CMA on-state, CMA & CR on-state and DDA on-state in turns from left-hand. In 64QAM mode, LMS, data signed and error signed LMS algorithm have a good CMA & CR characteristic. In 64QAM mode, data signed LMS and error signed LMS update have the same convergence characteristics as standard LMS update, while signed signed LMS update has the retarded convergence. In 256QAM mode, data signed LMS update has the similar convergence characteristic with standard LMS update. On the other hand, error signed and signed signed LMS update have the retarded convergence compared with standard LMS. In particular, they suffer from the performance degradation of convergence at CMA.

![64/256 QAM SER Plot](image)

**Fig.7** SER(Symbol Error Rate) of various LMS Algorithm
Fig. 8 MSE convergence curve. Multipath distortion of -16dB at 0.6us, -26dB at 1.2us, -36dB at 1.8us, and -56dB at 2.4us (256QAM).

Fig. 9 MSE convergence curve. Multipath distortion of -10dB at 0.6us, -20dB at 1.2us, -30dB at 1.8us, and -50dB at 2.4us (64QAM).

Fig. 8-9 shows 64QAM, 256QAM MSE convergence curve. LMS, data signed, error signed LMS has a similar MSE curve. But signed signed LMS has a very late convergence time in 64QAM and emission in 256QAM.

Table 2 when 2fs, 64QAM: 23.5dB, 256QAM: 30dB

Convergence Time

<table>
<thead>
<tr>
<th>Modulation</th>
<th>CR On (symbol)</th>
<th>DD On (symbol)</th>
</tr>
</thead>
<tbody>
<tr>
<td>LMS</td>
<td></td>
<td></td>
</tr>
<tr>
<td>64QAM</td>
<td>20,000</td>
<td>25,000</td>
</tr>
<tr>
<td>256QAM</td>
<td>25,000</td>
<td>30,000</td>
</tr>
<tr>
<td>Data Signed LMS</td>
<td></td>
<td></td>
</tr>
<tr>
<td>64QAM</td>
<td>20,000</td>
<td>25,000</td>
</tr>
<tr>
<td>256QAM</td>
<td>25,000</td>
<td>30,000</td>
</tr>
<tr>
<td>Error Signed LMS</td>
<td></td>
<td></td>
</tr>
<tr>
<td>64QAM</td>
<td>30,000</td>
<td>40,000</td>
</tr>
<tr>
<td>256QAM</td>
<td>45,000</td>
<td>60,000</td>
</tr>
<tr>
<td>Signed Signed LMS</td>
<td></td>
<td></td>
</tr>
<tr>
<td>64QAM</td>
<td>55,000</td>
<td>70,000</td>
</tr>
<tr>
<td>256QAM</td>
<td>75,000</td>
<td>---</td>
</tr>
</tbody>
</table>

LMS and data signed LMS have better convergence performance for CMA than error signed and signed signed LMS have. Thus Channel Estimator made poor decision CMA mode or DDA mode.

In Table 2 we summarize the convergence times of various LMS Algorithm. Standard LMS Algorithm is converged fast, so does comparatively data signed and error signed LMS. But signed signed LMS has a slower convergence, thus it is not proper for high speed application. LMS has a small step size, and step size of the data signed LMS is similar to LMS, but error signed and signed signed LMS have larger step size compared with LMS and data signed LMS.

4. CONCLUSION

In this paper, we simulated and compared the performance of various LMS algorithms in blind decision feedback equalizer for cable modem. According to the results, data signed and error signed is proper in 64QAM. If designers put up with late convergence time, signed signed LMS algorithm can be used. In 256QAM, LMS and data signed has a good performance, while error signed LMS and signed signed LMS algorithms have poor characteristics. Thus, we know that as goes to a high order QAM, error and signed signed LMS algorithms are improper in DFE.

In many cases, multipliers occupy a large portion of DFE. Thus, each LMS algorithms using signed representation of input and error value can attain to low hardware complexity and low power dissipation due to the reduced number of multipliers in coefficient update block. Simulation results shows the fact that data signed LMS satisfy the performance and low hardware complexity requirements. In conclusion, data-signed LMS algorithm is the optimum solution for FS-DFE having low hardware complexity suitable for the high order QAM Applications.

5. REFERENCES


