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# 연관성 귀환을 갖는 다중 훈련 LMS 기반의 결정 재입력 등화기

최윤석\* · 박형근\*\*

## Multiple-Training LMS based Decision Feedback Equalizer with Soft Decision Feedback

Yun-Seok Choi\* · Hyung-Kun Park\*\*

### 요 약

이동 멀티미디어 통신에서의 주요한 요소기술 중의 하나는 높은 품질의 서비스를 제공할 수 있는 광대역 신호전송기술이다. 이와 같은 광대역 이동통신 시스템을 위해서는 높은 주파수효율과 낮은 전력소모를 가지면서 시변 다중경로 페이딩 채널에 의한 신호왜곡을 극복해야 한다. 따라서 단일반송파의 짧은 버스트 데이터전송을 위한 적응적 결정귀환 등화방식이 하나의 해결책으로 고려되고 있다. 본 논문에서는 짧은 훈련심볼을 포함한 버스트신호를 갖는 시스템의 성능향상을 위하여 연관성 귀환을 갖는 MTLMS (multiple-training least mean square) 기반의 DFE(decision feedback equalizer)를 제안하고 시뮬레이션을 통하여 이동무선채널에서 그 성능을 분석한다.

### ABSTRACT

A key issue toward mobile multimedia communications is to create technologies for broadband signal transmission that can support high quality services. Such a broadband mobile communications system should be able to overcome severe distortion caused by time-varying multi-path fading channel, while providing high spectral efficiency and low power consumption. For these reasons, an adaptive suboptimum decision feedback equalizer (DFE) for the single-carrier short-burst transmissions system is considered as one of the feasible solutions. For the performance improvement of the system with the short-burst format including the short training sequence, in this paper, the multiple-training least mean square (MTLMS) based DFE scheme with soft decision feedback is proposed and its performance is investigated in mobile wireless channels throughout computer simulation.

### 키워드

MTLMS, Decision Feedback Equalizer, Soft Decision Feedback, Multi-Path Fading

### 1. 서 론

A key issue toward mobile multimedia communications is to create technologies for broad-

band signal transmission that can support high quality services. In such a broadband mobile communications system, the transmitted signal will be distorted severely by the time-varying

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\*삼성전자 네트워크사업부

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\*\*한국기술교육대학교 정보기술공학부

multi-path fading channel [1]~[2]. Therefore, a desired system should be designed to reject the severe inter-symbol interference caused by multi-path propagation and to be robust to time-varying fading, while providing high spectral efficiency and low power consumption. In many current mobile wireless systems as well as future mobile wireless packet data system, the short-burst transmissions are used to reduce transmission delay, and to limit the time variation of wireless channels over a burst [3]. However, training overhead is very significant for such short burst formats. So, the availability of the short training sequence and the fast converging adaptive algorithm is essential in the system adopting the symbol-by-symbol adaptive equalizer.

The recursive least squares (RLS)-type algorithms have been used commonly because these algorithms provide a fast converging property [4],[5]. But, these algorithms require high computational complexity and also provide a numerical instability when the eigenvalue spread of the input correlation matrix is large [6]. As a consequence, the RLS based equalizer consumes a large amount of the computational power at the receiver. By contrast, the least mean square (LMS) algorithm has low computational complexity but the convergence is very slow when the eigenvalue spread of the input correlation matrix is large [7]. A MTLMS algorithm has been known as an effective adaptive algorithm [6] that can provide the desired converging performance with a competitive computational complexity in such short-burst transmissions with a short training sequence. This algorithm has mitigated the problem of the slow convergence by using the multiple-training method, i.e., the reuse of the received training symbols and of the numerical instability by regularizing the solution of the adaptive coefficient vector such that the sensitivity to small eigenvalues is minimal while this capability is absent from the conventional LMS algorithm. Recently this MTLMS algorithm has been applied to the mobile wireless communications system, especially IS-136 receiver [8].

In this paper, to mitigate the effect of error propagation and provide robustness at low SNRs, we propose MTLMS based DFE with a simple soft decision feedback device and investigate the performance of the equalizer according to the iterations parameter, the length of the training sequence and the Doppler frequency in mobile wireless channels throughout the computer simulations.

This paper is organized as follows: In Section II, we describe the scheme of MTLMS based DFE and for the performance analysis, transceiver model and wireless channel are modeled in Section III. In Section IV, computer simulations are executed and their results are discussed. Finally, in Section V, concluding remarks are presented.

## II. MTLMS Based DFE with Soft Decision Feedback

### 1. MTLMS Based DFE

Let the burst format be composed of the training sequence and the message sequence. If the DFE using the MTLMS algorithm is in the training mode, the received training sequence is repeatedly trained up to a pre-assigned iteration number,  $K$ . Then the tracking mode is operated to acquire the equalized message sequence. In the training mode, the DFE tap coefficients are acquired from the last iteration. In the tracking mode, the message symbols are equalized with these converged DFE tap coefficients as its initials. In [8], the MTLMS algorithm was also used extensively in the tracking mode for exploring fully the decision information. However, the performance improvement is very slight but the complexity is increased. So, this operation is not considered.

In the MTLMS based DFE, the DFE output  $\hat{a}^q(n)$  at the  $q$ -th iteration,  $1 \leq q \leq K$  for training and  $q=1$  for tracking, is given by

$$\hat{a}^q(n) = \sum_{i=0}^{N_T-1} g_i^q(n;i)r(n-i) + \sum_{j=1}^{N_b} g_b^q(n;j)d^q(n-j) \quad (1)$$

where  $g_f^q(n; i)$  and  $g_b^q(n; j)$  represent the feed-forward filter (FFF) and feedback filter (FBF) tap coefficients at  $q$ -th iteration, respectively.  $N_f$  and  $N_b$  are the length of FFF and FBF, respectively.  $d^q(n-j)$  represents the feedback symbol which is the known symbol  $a(n-j)$  for training mode and the previously detected hard- or soft-decision symbol  $\tilde{a}^q(n-j)$  for tracking mode. Note that  $r(n-i)$  is the received signal which has the same value for all iterations and so the  $q$  can be dropped. The DFE tap update equation using MTLMS at the  $q$ -th iteration can be represented as

$$g_f^q(n+1; i) = g_f^q(n; i) + \mu_f e^q(n) x^*(n-i)$$

for  $i = 0, 1, \dots, N_f - 1$  (2)

$$g_b^q(n+1; j) = g_b^q(n; j) + \mu_b e^q(n) d^{q*}(n-j)$$

for  $j = 1, 2, \dots, N_b$  (3)

where the superscript  $*$  denotes the complex conjugation and  $\mu_f$  and  $\mu_b$  represent the FFF step size and the FBF step size, respectively.  $x(n-i)$  is the  $i$ th power normalized output element of the received sequence and given by

$$x(n-i) = r(n-i) / \sqrt{\varepsilon + P(n; i)} \quad (4)$$

where  $P(n; i)$  is the instantaneous power estimate of  $r(n-i)$  and  $\varepsilon$  is a small constant that eliminate overflow when the value of  $P(n; i)$  are very small. For computing the values of  $P(n; i)$ , the exponential weighted method was used.

$$P(n; i) = \beta P(n-1; i) + (1-\beta) |r(n-i)|^2 \quad (5)$$

where  $\beta$  is the forgetting factor between 0 and 1. The error signal is computed by

$$e(n) = \hat{a}^q(n) - d^q(n) \quad (6)$$

In the MTLMS algorithm, note that the initial weight vector at  $q$ th iteration is the same as the

last updated weight vector at  $(q-1)$ th iteration. In addition, the term "normalized" was dropped for convenience. The performance of the MTLMS based DFE becomes better with the increase of the iterations number  $K$ . However, the computational complexity also increases linearly with  $K$ . The MTLMS algorithm has several merits over other algorithms such as LMS and RLS [6]. The MTLMS algorithm can permit the faster tracking performance than the LMS algorithm in the time-varying channel. In addition, because the MTLMS algorithm performs regularization in solving for the adaptive coefficients, it is more robust to noise for spectrally nulled data than LMS algorithm. The RLS algorithm was shown to have instability and noise amplification properties that are traceable to the large eigenvalue spread of the data correlation matrix. But, the MTLMS algorithm does not suffer from these problems.

## 2. Simple Soft Decision Feedback

The problem of a DFE approach is the error propagation. In this section, the simple soft decision feedback device is described. While the optimum soft feedback is estimated using maximum a posteriori probability (MAP) algorithms, the simple soft decision method is acquired by approximating the optimum approach and requires only the simple operation of passing the DFE output through a (soft) nonlinear function.

Note that although the a posteriori probability of  $a(n)$  is, in general, a function of all available observations, it is the current observation  $\hat{a}(n)$  that contributes the most to the value of this probability (since  $\hat{a}(n)$  is the equalized output corresponding to  $a(n)$ ). Thus, it is assumed that the soft feedback  $\hat{a}(n)$  is a function only of the current observation  $a(n)$ . Accordingly,

$$\tilde{a}(n) = E[a(n) | \hat{a}(n)] = \sum_{v_a(n)} a(n) P(a(n) | \hat{a}(n)) \quad (7)$$

and

$$P(a(n) | \hat{a}(n)) = \frac{P(a(n), \hat{a}(n))}{P(\hat{a}(n))} = \frac{P(\hat{a}(n) | a(n)) P(a(n))}{\sum_{v_a(n)} P(\hat{a}(n) | a(n)) P(a(n))} \quad (8)$$

where the a priori probability  $P(\hat{a}(n) | a(n))$  can be given as

$$P(\hat{a}(n) | a(n)) = \frac{1}{\sqrt{\pi} \gamma} \text{Exp}(-\gamma |\hat{a}(n) - a(n)|^2) \quad (9)$$

where  $\gamma$  is the signal to ISI-plus-noise ratio. Using Eq. (7), (8) and (9), and assuming that  $a(n)$  is QPSK, the following soft decision function is obtained:

$$\tilde{a}(n) = f(\hat{a}(n)) = \frac{1}{\sqrt{2}} (\tanh(\sqrt{2}\gamma \text{Re}(\hat{a}(n))) + j \tanh(\sqrt{2}\gamma \text{Im}(\hat{a}(n)))) \quad (10)$$

Soft feedback is obtained simply by passing the real part and the imaginary part of the DFE output through a hyperbolic tangent function. This method requires the knowledge of the signal to ISI-plus-noise ratio,  $\gamma$ . However, an appropriate fixed value of  $\gamma$  can be chosen without greatly affecting the achievable performance of the soft-feedback DFE.

### III. Channel and System Model for Simulation

Mobile radio channels can be modeled as multipath Rayleigh fading channels having an impulse response  $h(t; \tau) = \sum_{l=0}^{L-1} \alpha_l(t) \delta(\tau - \tau_l)$  where the coefficient  $\alpha_l(t)$  is the  $l$ -th multipath gain which is modeled as complex Gaussian random processes with zero mean. Under the assumption of wide sense stationary uncorrelated scattering and a common time selective correlation function across the delay profile, the autocorrelation function yields

$$E[h(t; \tau) h^*(t'; \tau')] = P_h(\tau) \delta(\tau - \tau') \rho(t - t') \quad (11)$$

where the superscript  $*$  denotes the complex conjugation,  $P_h$  the delay power spectral density or the power delay profile, and  $\rho$  the time selective correlation function, normalized to unit power, that is  $\rho(0)=1$ . A standard version of  $\rho$ , which is derived under the assumption of isotropic scattering, is used as

pic scattering, is used as

$$\rho(t - t') = J_0(2\pi f_d(t - t')) \quad (12)$$

where  $f_d$  is the one-sided Doppler spread and  $J_0$  denotes the zeroth-order Bessel function of the first kind. It is assumed that the path delay is integer multiples of  $T_s$ , i.e.,  $\tau_l = T_s, l=0,1,\dots,L-1$ . In addition, the channel gain is normalized, i.e.,  $\sum_{l=0}^{L-1} E[|\alpha_l(t)|^2] = \sum_{l=0}^{L-1} P_l = 1$ . The minimum phase channel  $h_1(t; \tau)$ , and the nonminimum phase channel  $h_2(t; \tau)$ , models are considered and their power delay profiles are given in Table 1. For convenience of notation, the parameter  $\tau$  is dropped in  $h_i(t; \tau)$ ,  $i=1,2$ . Note that these channel coefficients are similar to COST-207 channel coefficients used in [10]. The channel  $h_1(t)$  has the time dispersion of  $3T_s$  and the minimum phase property. The channel  $h_2(t)$ , which represents more severely distorted ISI channel, has the time dispersion of  $8T_s$  and the non minimum phase property. It is shown that  $h_2(t)$  has the severe frequency selectivity and gives the worse channel than  $h_1(t)$ .

Table 1. Power delay profiles

Path (l)	$h_1(t; \tau)$ : 4-path minimum phase channel model		$h_2(t; \tau)$ : 9-path nonminimum phase channel model	
	Delay, $\tau_l$	Average power, $P_l$	Delay, $\tau_l$	Average power, $P_l$
0	0	0.575	0	0.213
1	$T_s$	0.362	$T_s$	0.405
2	$2T_s$	0.057	-	-
3	$3T_s$	0.006	$3T_s$	0.263
8	-	-	$8T_s$	0.119

For representing the time-variation of the mobile radio channel, the symbol-normalized fade rate  $f_d T_s$  is the useful index, where  $f_d$  is the maximum Doppler frequency and  $T_s$  is the symbol duration. However, in a channel structure which incorporates periodic transmission of training bits,  $f_d T_s$  is an incomplete measure of the

rate at which the channel varies. Since the training and tracking of the channel is performed during the transmission of the TDMA slot, the slot-normalized fade rate is used as a fading channel index and is defined as [6]

$$\kappa = f_d T_{slot} = f_d N_s T_s \quad (11)$$

where  $T_{slot}$  is the slot duration and  $N_s$  is the number of symbols per time slot. This number represents the rough average number of occurrences of deep fades per time slot.

A QPSK signal is transmitted. Each transmitted burst contains the training sequence of variable length  $A$  and the message sequence of the length of 144 (only for the purpose of the simulation). The length of the training sequence are 12, 16, 20, 24, 28, 32 and 64 which correspond to the overhead of about 7.7%, 10%, 12.2%, 14.3%, 16.3%, 18% and 31%, respectively. Note that the small overhead represents high spectral efficiency.

The carrier frequency is 5GHz and the channel bandwidth is 1MHz. The symbol interval is 1 $\mu$ s. For 4-path channel model  $h_1(t)$ , the FFF length was set to be 7 and the FBF length was set to be 4. For 9-path channel model  $h_2(t)$ , the FFF length was set to be 11 and the FBF length was set to be 9. The FFF step size was 0.05 and the FBF step size was 0.005 for both channels. For the soft decision feedback DFE,  $\gamma=5$ dB is used [9].

## IV. Performance Results

### 1. Computational Complexity Comparison

In Table 2, the computational complexities of the MTLMS, RLS, fast RLS (FRLS), LMS, and power-normalized LMS (NLMS) algorithms are compared in terms of the number of operations per input sample for training mode.

$N$  denotes the number of equalizer tap coefficients. The extensive computer simulations have been carried out to compare and evaluate the performance of the MTLMS based DFE with hard or soft decision feedback.

### 2. Simulation Results

Table 2. Complexity comparisons of various algorithms

Algorithms	Complex multiplications	Complex division
MTLMS	$K(2N+1)$	$N$
RLS	$2.5N^2 + 4.5N$	2
FRLS	$20N+5$	3
LMS	$2N+1$	0
NLMS	$2N+1$	$N$

Since the MTLMS algorithm is the block-iterative algorithm, the performance of a MTLMS based DFE depends on the iterations parameter ( $K$ ) and the length of the training sequence ( $A$ ). Therefore, the effects of the iterations parameter ( $K$ ) and the length of training sequence ( $A$ ) on the BER performance are investigated. The slow fading channel with a normalized Doppler frequency of 0.00012 ( $f_d=120$ ) was assumed. This implies that the minimum time between the two fading nulls is 4.2ms ( $1/2f_d$ ) [11], which is much longer than the considered maximum burst length of 208 $\mu$ s (this is in the case of  $A=64$ ). The SNR ( $E_b/N_0$ ) was 18dB.

Figs. 1 and 2 show the BER performance of a MTLMS based DFE as a function of the iterations parameter ( $K$ ) in  $h_1(t)$  and  $h_2(t)$ , respectively. It is shown that the performance is improved as the value of  $K$  increases while the computational complexity is proportional to  $K$ . In  $h_1(t)$ , when  $K$  is increased from one to four, a large improvement is obtained. However, the improvement is saturated when  $K$  is further increased. In  $h_2(t)$ , since the FFF step size of 0.05 is not small enough to achieve the stable MSE performance, the BER performance is also not stable. To achieve the stable performance, a smaller FFF step size is needed. However, since the large FFF step size can give the faster converging performance and the smaller complex multiplications, the FFF step size of 0.05 is hold. In severely distorted channel,  $h_2(t)$ , a MTLMS based DFE with the soft decision feedback shows the better performance than a MTLMS based DFE with the hard decision feedback at SNR of 18dB. However, in good channel,  $h_1(t)$ , the di-

ferences of the performance are very slight. Fig. 3 shows the BER performance of a MTLMS based DFE as a function of the length of the training sequence ( $A$ ) in both channel environments. It is shown that the performance becomes better as  $A$  increases. The reason is that the larger  $A$  gives the more sufficient channel information. But, note that spectral efficiency is lowered as  $A$  increases. Figs. 4 and 5 show the BER performance of a MTLMS based DFE as a function of a slot-normalized Doppler frequency in  $h_1(t)$  and  $h_2(t)$ , respectively. As a normalized Doppler frequency increases, the BER performance becomes worse. Note that the performance of a DFE with the largest  $K$  goes through the faster degradation. The reason is that the

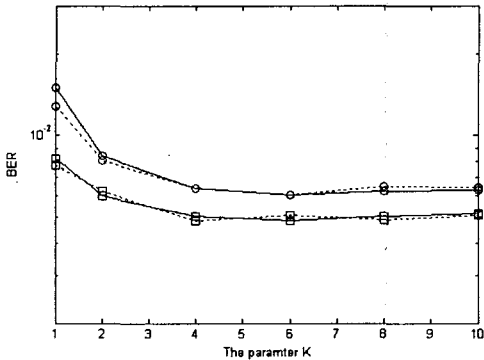


Fig. 1. BER performance according to the iterations parameter,  $K$ , in  $h_1(t)$ . Solid line: hard decision; Dotted line: soft decision, Circle: 16 training; Square: 32 training.

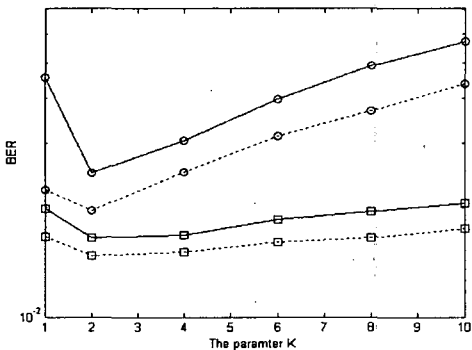


Fig. 2. BER performance according to the iterations parameter,  $K$ , in  $h_2(t)$ . Solid line: hard decision; Dotted line: soft decision, Circle: 16 training; Square: 32 training.

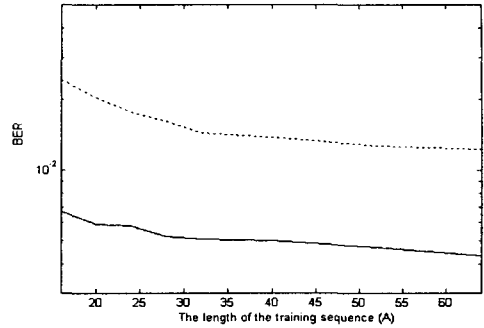


Fig. 3. BER performance according to the length of the training sequence,  $A$ ,  $K=4$ , Soft decision feedback, Solid line:  $h_1(t)$  Dotted line:  $h_2(t)$ .

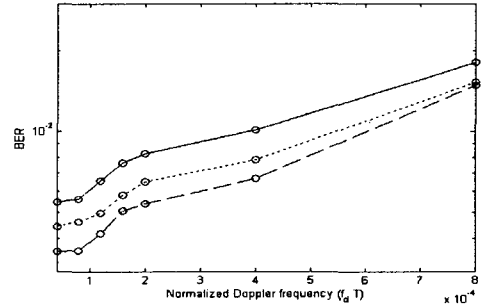


Fig. 4. BER performance according to the normalized Doppler frequency in  $h_1(t)$ .  $K=4$ , Soft decision feedback, Solid line: 16 training; Dotted line: 32 training; Dashed line: 64 training.

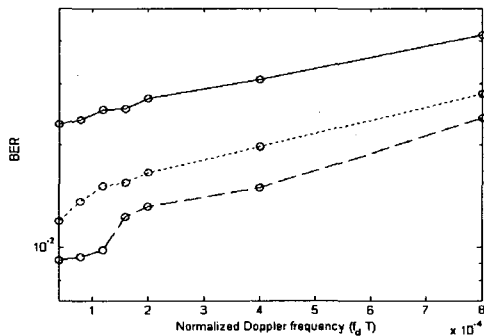


Fig. 5. BER performance according to the normalized Doppler frequency in  $h_2(t)$ .  $K=4$ , Soft decision feedback, Solid line: 16 training; Dotted line: 32 training; Dashed line: 64 training.

TDMA slot with the larger  $K$  has a more chance of a deep fade during a given transmit time and the TDMA slot of a deep fade cannot be

equalized reliably.

### V. Conclusion

The MTLMS algorithm has mitigated the problem of the slow convergence by using the multiple-training method with a competitive computational complexity in such short-burst transmissions by using a short training sequence. Soft decision feedback device can mitigate the effect of error propagation and provide robustness at low SNR. With these attractive features, in this paper, a MTLMS based DFE method with soft decision feedback was proposed and its performance was investigated in mobile wireless channels throughout the computer simulations. Simulation results show that the better performance can be achieved as the length of the training sequence increases, but the spectral efficiency is lowered and the system becomes weaker to time-varying fading. The more training sequences are required in the higher normalized Doppler frequency, and MTLMS with soft decision feedback shows better BER performance than the case of hard decision.

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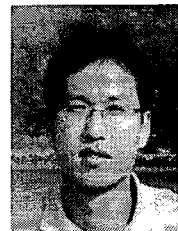
### 저자소개

#### 최윤석(Yun Seok Choi)



1997년 2월 : 고려대학교 전자공학과 졸업  
 1999년 8월 : 고려대학교 전자공학과 석사  
 2004년 2월 : 고려대학교 전자공학과 박사  
 2004. 3~현재 : 삼성전자 정보통신총괄 네트워크사업부 책임연구원  
 ※관심분야 : 디지털 통신 시스템, 이동무선통신

#### 박형근(Hyung-Kun Park)



1995년 2월 : 고려대학교 전자공학과 (공학사)  
 1997년 2월 : 고려대학교 전자공학과 (공학석사)  
 2000년 8월 : 고려대학교 전자공학과 (공학박사)  
 2000년 9월~2001년 8월 : University of Colorado at Colorado Springs, Postdoc.  
 2001년 9월~2004년 2월 : 현대시스템, 선임연구원  
 2004년 3월~현재 : 한국기술교육대학교 정보기술공학부 전임강사  
 ※관심분야 : 4세대 이동통신, OFDM, 무선자원관리