MTLMS 기반의 결정귀환 등화기의 설계

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Design of MTLMS based Decision Feedback Equalizer

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요 약

다음은 요약문 입이동 멀티미디어 통신에서의 주요한 요소기술 중의 하나는 높은 품질의 서비스를 제공할 수 있는 광대역 전송기술이다. 이와 같은 광대역 이동통신시스템을 위해서는 높은 주파수 효율과 낮은 전력소모를 가지면서 시변 다중경로 페이딩 채널에 의한 신호왜곡을 극복해야 한다. 따라서 단일 반송파의 짧은 버스트 데이터전송을 위한 적응적 결정귀환 등화방식이 하나의 해결책으로 고려되고 있다. 본 논문에서는 짧은 훈련심볼을 포함한 버스트 신호 갖는 시스템의 성능향상을 위하여 연판정 귀환을 갖는 MTLMS (multiple-training least mean square) 기반의 DFE(decision feedback equalizer)를 제안하고 시뮬레이션을 통하여 다른 등화방식과의 성능을 비교 분석하였다.

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

Decision Feedback Equalizer, multiple-training, DFE

Ⅰ. Introduction

The recursive least squares (RLS)-type algorithms have been used commonly because these algorithms provide a fast converging property. But, these algorithms require high computational complexity and also provide a numerical instability when the eigenvalue spread of the input correlation matrix is large [1]. 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. A multiple-training LMS (MTLMS) algorithm has been known as an effective adaptive algorithm [1] 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 [2].

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 andthe Doppler frequency in mobile wireless channels throughout the computer simulations.

II. Multiple-training LMS 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 [2], the MTLMS algorithm was also used extensively in the tracking mode for exploring fully the decision information. However, the performance improvement is very slightbut 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, $1 \le q \le K$ for training and q=1 for tracking, is given by

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

where $g_f^q(n;i)$ and $g_f^q(n;j)$ represent the feedforward filter (FFF) and feedback filter (FBF) tap coefficients at qth 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 superscript q can be dropped. The DFE tap update equation using MTLMS algorithm at the q-th iteration can be represented as

$$g_f^q(n+1;i) = g_f^q(n;i) + \mu_f e^q(n) x^*(n-i) \quad i = 0,1,\cdots,N_f-1 \tag{2}$$

$$g_b^q(n+1;j) = g_b^q(n;j) + \mu_b e^q(n) d^{q*}(n-j) \quad j = 1,2,\cdots,N_b \tag{3}$$

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

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

where $P(n;i)$ is the instantaneous power estimate of $r(n-i)$ and ε 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 as follows

$$P(n;i) = \beta P(n-1;i) + (1-\beta)\left|r(n-i)\right|^2 \tag{5}$$

where β is the forgetting factor between 0 and 1. The error signal is computed by

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

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 [1]. 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.

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 $\tilde{a}(n)$ is a function only of the current observation $a(n)$. Accordingly,

$$\tilde{a}(n) = E[a(n) \mid \hat{a}(n)] = \sum_{\forall a(n)} a(n)P(a(n) \mid \hat{a}(n)) \tag{7}$$

and

$$P(a(n) \mid \hat{a}(n)) = \frac{P(a(n), \hat{a}(n))}{P(\hat{a}(n))} = \frac{P(\hat{a}(n) \mid a(n))P(a(n))}{\sum_{\forall a(n)} P(\hat{a}(n) \mid a(n))P(a(n))} \tag{8}$$

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

$$P(\hat{a}(n) \mid a(n)) = \frac{1}{\sqrt{\pi / \gamma}} Exp(-\gamma \mid \hat{a}(n) - a(n) \mid^2) \tag{9}$$

where γ 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:

$$\tilde{a}(n) = f(\hat{a}(n)) = \frac{1}{\sqrt{2}}\left(\tanh(\sqrt{2}\gamma \operatorname{Re}(\hat{a}(n))\right) + j \tanh\left(\sqrt{2}\gamma \operatorname{Im}(\hat{a}(n))\right) \tag{10}$$

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,γ,. However, an appropriate fixed value of γcan be chosen without greatly affecting the achievable performance of the soft-feedback DFE.

III. Simulation and Results

Mobile radio channels can be modeled as multipath Rayleigh fading channels. Coefficients of power delay profiles are COST-207 channel coefficients used in [3] (some modification is done for urban model).

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 carrier frequency is 5GHz and the channel bandwidth is 1MHz. For channel model 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, γ=5dB is used [4].

In Table 1, 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.

Table 1. 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.

Fig. 1 shows the BER performance of a MTLMS based DFE as a function of the iterations parameter (K). It is shown that the performance is improved as the value of K increases while the computational complexity is proportional to K. 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. 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.

Fig. 2 shows the BER performance of a MTLMS based DFE as a function of a slot-normalized Doppler frequency. 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 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.

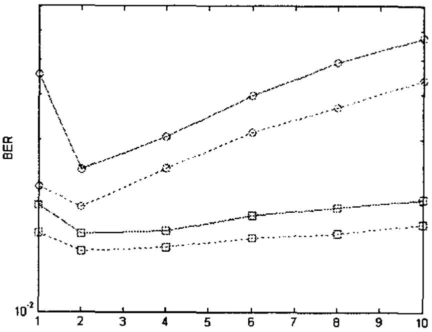

Fig. 1 BER performance of a MTLMS based DFE as a function of the iterations parameter (K). $SNR = 18dB$, $f_d T_s = 0.00012$, Solid line: hard decision; Dotted line: soft decision, Circle: 16 training; Square: 32 training

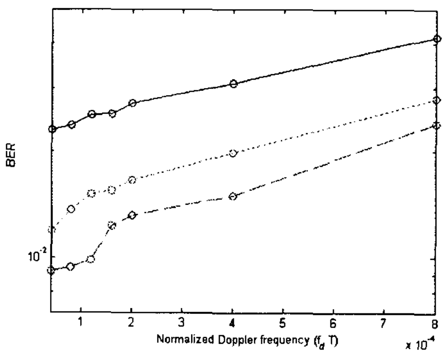

Fig. 2 BER performance of a MTLMS based DFE as a function of the normalized Doppler frequency. K=4, $SNR = 18dB$, Soft decision feedback, Solid line: 16 training; Dotted line: 32 training; Dashed line: 64 training.

IV. 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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