An Adaptive MLSE Receiver for TDMA Systems: A Hybrid of Per-Survivor Processing and Tentative Decision MLSE

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Abstract - An adaptive maximum likelihood sequence estimation (MLSE) receiver employing both the per-survivor processing (PSP)-MLSE and the tentative decision (TD)-MLSE, and selecting either one of them depending on the received signal power is proposed. The received signal power is estimated by using a channel estimate, assuming that M-ary PSK symbols are transmitted. Simulation results demonstrate that the proposed MLSE can significantly reduce the computational complexity with little degradation in performance, as compared with the conventional PSP-MLSE.

I. Introduction

MLSE has been recognized as a powerful technique for detecting information sequences transmitted over fading channels in time division multiple access (TDMA) communication systems. MLSE is implemented by means of the Viterbi algorithm (VA), using the channel impulse response estimated from a training sequence. Adaptive MLSE is an extension of the MLSE algorithm. By updating channel parameters at each time, adaptive MLSE can track fast fading channels and outperform the conventional MLSE. The adaptive MLSE algorithms in [1]-[4], which will be referred to as the *tentative decision* (TD)-MLSE, use some tentative decision values for channel update; as a consequence, their tracking behavior tends to be degraded by the decision delay inherent in the VA. To overcome this difficulty, adaptive MLSE algorithms that update channel parameters for the survivor of each state in the VA have been introduced [5]-[7]. These algorithms eliminate the decision delay via *per-survivor processing* (PSP), and are referred to as the PSP-MLSE. It has been observed that the PSP-MLSE is very effective in tracking fast fading channels. However, updating channel parameters for each survivor often requires extremely heavy computation, which limits the use of the PSP-MLSE.

In this paper, we propose a simple but efficient method to reduce the complexity of the PSP-MLSE. The proposed method, called the *hybrid*-MLSE, employs both the PSP-MLSE and TD-MLSE and at each time selects one of them by comparing an estimate of the received signal power with a threshold. The instantaneous signal power is estimated by using an estimate of the channel impulse response, assuming that M-ary PSK symbols are transmitted. It is shown through computer simulation that the hybrid-MLSE can significantly reduce the computational complexity with little degradation in performance, as compared with the PSP-MLSE.

II. System Model And MLSE Algorithms

The baseband system model considered in this paper is shown in Fig. 1. Here, d_n represents an M-ary PSK (or DPSK) symbol with $|d_n| = 1$; $g(t)$ is the transmit pulse shape; $\eta(t)$ is additive white Gaussian noise (AWGN). The output of the receiver filter sampled at $t = kT$ is

$$r_k = \sum_{n=0}^{L-1} d_{k-n} \cdot h_{k,n} + \eta_k \quad (1)$$

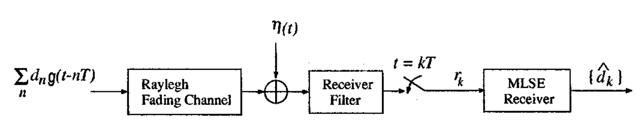

Fig. 1. Baseband System Model.

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where $h_{k,n}$ is the impulse response of the equivalent channel at time k due to an impulse that was applied at n time units earlier: it describes $g(t)$, the Rayleigh fading channel and the receive filter in the discrete time domain, and its total length is denoted by L. In matrix notation

$$r_k = \mathbf{d}_k^T \mathbf{h}_k + \eta_k \tag{2}$$

where $\mathbf{d}_k = [d_k, d_{k-1}, \ldots, d_{k-L+1}]^T$, $\mathbf{h}_k = [h_{k,0}, h_{k,1}, \ldots, h_{k,L-1}]^T$ and the superscript T denotes transposition.

The adaptive MLSE can be efficiently implemented by using the VA with M^{L-1} states and a channel estimator. Each state $\mathbf{s}_i$ in the VA consists of $(L-1)$ M-ary symbols, expressed as $\mathbf{s}_i = [s_{i,1}, s_{i,2}, \ldots, s_{i,L-1}]$. The transition from the state $\mathbf{s}_i$ to $\mathbf{s}_j$ can occur if $s_{i,l} = s_{j,l+1}$ for $1 \leq l \leq L-2$. The corresponding transition vector $\mathbf{x}(\mathbf{s}_i, \mathbf{s}_j)$ is defined as

$$\begin{aligned} \mathbf{x}(\mathbf{s}_i, \mathbf{s}_j) &= [s_{j,1}, s_{i,1}, \ldots, s_{i,L-2}, s_{i,L-1}]^T \\ &= [s_{j,1}, s_{j,2}, \ldots, s_{j,L-1}, s_{i,L-1}]^T \,. \end{aligned} \tag{3}$$

The number of possible transition vectors is M^L and $\mathbf{d}_k$ in (2) is one of them. If the estimate $\hat{\mathbf{h}}_k$ of the channel parameter $\mathbf{h}_k$ is given, the VA computes the branch metric $|r_k - \mathbf{x}(\mathbf{s}_i, \mathbf{s}_j)^T \cdot \hat{\mathbf{h}}_k|^2$ for each transition. Based on the branch metrics, the VA determines a survivor, a path with the smallest metric, for each state.

For the computation of the branch metrics at time $k+1$, the TD-MLSE estimates $\hat{\mathbf{h}}_{k+1}$ by using a tentative decision value obtained by tracing back the path associated with the survivor with the smallest metric at time k. Increasing the duration, say D, of backtracing decreases the probability of decision error, but degrades the channel tracking performance (D is called the decision delay). If the recursive least squares (RLS) algorithm is applied to the channel estimation, which is the case of this paper, then $\hat{\mathbf{h}}_{k+1}$ is obtained by

$$\hat{\mathbf{h}}_{k+1} = \hat{\mathbf{h}}_k + \mathbf{G}_{k+1} \cdot [r_{k-D} - \hat{\mathbf{d}}_{k-D}^T \cdot \hat{\mathbf{h}}_k] \tag{4}$$

$$\Phi_{k+1}^{-1} = \lambda^{-1}[\Phi_k^{-1} - \mathbf{G}_{k+1}\hat{\mathbf{d}}_{k-D}^H \Phi_k^{-1}] \tag{5}$$

$$\mathbf{G}_{k+1} = \frac{\lambda^{-1}\Phi_k^{-1}\hat{\mathbf{d}}_{k-D}}{1+\lambda^{-1}\hat{\mathbf{d}}_{k-D}^H \Phi_k^{-1}\hat{\mathbf{d}}_{k-D}} \tag{6}$$

where the superscript H denotes the Hermitian transposition; λ is the forgetting factor and $\hat{\mathbf{d}}_{k-D}$ is the tentative symbol vector at time $k-D$ assumed by the survivor with the smallest metric at time k. Φ_k is the L-by-L correlation matrix and Φ_k^{-1} is updated by using the *Riccati equation* for the RLS algorithm in (5) [8].

The PSP-MLSE updates the channel parameters for all M^{L-1} states. Let $\{\hat{\mathbf{h}}_k(\mathbf{s}_i), i = 1, \ldots, M^{L-1}\}$ be the set of estimates of $\mathbf{h}_k$ for the transition vectors started from the state $\mathbf{s}_i$ at time $k-1$. VA computes the branch metric $|r_k - \mathbf{x}(\mathbf{s}_i, \mathbf{s}_j)^T \cdot \hat{\mathbf{h}}_k(\mathbf{s}_i)|^2$ for each transition at time k and determines a survivor for each state. The estimate $\hat{\mathbf{h}}_{k+1}(\mathbf{s}_i)$ is obtained under the assumption that the survivor of $\mathbf{s}_i$ at time k yields the correct symbol vector. To describe the RLS recursion for the PSP-MLSE, we consider a state $\mathbf{s}_i$ at time k and a state $\mathbf{s}_{i_o}$ at time $k-1$ where $i_o \in \{1, 2, \ldots, M^{L-1}\}$ and $\mathbf{s}_{i_o}$ is the state for which the path from $\mathbf{s}_{i_o}$ to $\mathbf{s}_i$ yields the smallest branch metric, among the M paths entering the state $\mathbf{s}_i$. For each state $\mathbf{s}_i$, $\hat{\mathbf{h}}_{k+1}(\mathbf{s}_i)$ is obtained by

$$\hat{\mathbf{h}}_{k+1}(\mathbf{s}_i) = \hat{\mathbf{h}}_k(\mathbf{s}_{i_o}) + \mathbf{G}_{k+1}(\mathbf{s}_i) \cdot [r_k - \hat{\mathbf{d}}_k(\mathbf{s}_i)^T \cdot \hat{\mathbf{h}}_k(\mathbf{s}_{i_o})] \tag{7}$$

$$\Phi_{k+1}^{-1}(\mathbf{s}_i) = \lambda^{-1}[\Phi_k^{-1}(\mathbf{s}_{i_o}) - \mathbf{G}_{k+1}(\mathbf{s}_i)\hat{\mathbf{d}}_k^H(\mathbf{s}_i)\Phi_k^{-1}(\mathbf{s}_{i_o})] \tag{8}$$

$$\mathbf{G}_{k+1}(\mathbf{s}_i) = \frac{\lambda^{-1}\Phi_k^{-1}(\mathbf{s}_{i_o})\hat{\mathbf{d}}_k(\mathbf{s}_i)}{1+\lambda^{-1}\hat{\mathbf{d}}_k(\mathbf{s}_i)^H \Phi_k^{-1}(\mathbf{s}_{i_o})\hat{\mathbf{d}}_k(\mathbf{s}_i)} \tag{9}$$

where $\hat{\mathbf{d}}_k(\mathbf{s}_i)$ is the symbol vector at time k assumed by the survivor of $\mathbf{s}_i$.

III. Hybrid-MLSE Receiver

Referring to (2), a conditional expectation of the received signal power at time k is given by

$$P_k = E[(\mathbf{d}_k^T \mathbf{h}_k)^H (\mathbf{d}_k^T \mathbf{h}_k) | \mathbf{h}_k] \tag{10}$$

where $E[X|Y]$ denotes the conditional expectation of X given Y. Since $|d_i| = 1$ and $E[d_i^* d_j] = 0$, for $i \neq j$,

$$P_k = \mathbf{h}_k^H \mathbf{h}_k. \tag{11}$$

Note that P_k is still a random variable, because $\mathbf{h}_k$ is random; we shall assume $E[P_k] = 1$. The hybrid-MLSE evaluates the signal power estimate $\hat{P}_k$ by using the relation in (11), and employs the TD-MLSE if $\hat{P}_k$ is greater than a pre-determined threshold T_H and the PSP-MLSE, otherwise. To describe some details of the algorithm, we consider the following cases.

Case 1 (switching from TD-MLSE to PSP-MLSE). Suppose that switching from the TD-MLSE to the

PSP-MLSE occurs at time n (this means $\hat{P}_{n-1} > T_H$ and $\hat{P}_n < T_H$). To obtain $\hat{\mathbf{h}}_{n+1}(\mathbf{s}_i)$ for each state $\mathbf{s}_i$ by using (7)-(9), we set $\hat{\mathbf{h}}_n(\mathbf{s}_i) = \hat{\mathbf{h}}_n$ and $\Phi_n^{-1}(\mathbf{s}_i) = \Phi_n^{-1}$ for all $\mathbf{s}_i$ where $\hat{\mathbf{h}}_n(\mathbf{s}_i)$ and $\Phi_n^{-1}(\mathbf{s}_i)$, respectively, are the channel estimate and the inverse of the correlation matrix required for computing branch metrics at time n and for evaluating $\hat{\mathbf{h}}_{n+1}(\mathbf{s}_i)$; $\hat{\mathbf{h}}_n$ and Φ_n^{-1} are the estimates already obtained from the TD-MLSE. After evaluating $\hat{\mathbf{h}}_{n+1}(\mathbf{s}_i)$ for all $\mathbf{s}_i$, the signal power P_{n+1} is estimated by using one of the channel estimates which appears more accurate than the others. Specifically, for the PSP-MLSE the signal power is estimated as

$$\hat{P}_{k+1} = \hat{\mathbf{h}}_{k+1}(\hat{\mathbf{s}}^k)^H \hat{\mathbf{h}}_{k+1}(\hat{\mathbf{s}}^k) \tag{12}$$

where $\hat{\mathbf{s}}^k$ is the state associated with the smallest metric at time k. Use of (7)-(9), and (12) continues as long as $\hat{P}_k < T_H$, for $k \geq n+1$.

Case 2 (switching from PSP-MLSE to TD-MLSE). Suppose that switching from the PSP-MLSE to the TD-MLSE occurs at time n ($\hat{P}_{n-1} < T_H$ and $\hat{P}_n > T_H$). To compute branch metrics at time n and evaluate $\hat{\mathbf{h}}_{n+1}$ by using (4)-(6), we set $\hat{\mathbf{h}}_n = \hat{\mathbf{h}}_n(\hat{\mathbf{s}}^{n-1})$ and $\Phi_n^{-1} = \Phi_n^{-1}(\hat{\mathbf{s}}^{n-1})$ where $\hat{\mathbf{h}}_n(\hat{\mathbf{s}}^{n-1})$ and $\Phi_n^{-1}(\hat{\mathbf{s}}^{n-1})$ are the estimates associated with the state $\hat{\mathbf{s}}^{n-1}$ having the smallest metric at time $n-1$ of the PSP-MLSE. Use of (4)-(6) continues as long as $\hat{P}_k > T_H$, for $k \geq n+1$.

Case 3 (startup). Suppose that an initial channel estimate $\hat{\mathbf{h}}_1$, which may be estimated from a training sequence, is given. If $\hat{P}_1 = \hat{\mathbf{h}}_1^H \hat{\mathbf{h}}_1 > T_H$, then (4)-(6) are used for evaluating $\hat{\mathbf{h}}_2$. Otherwise, as in Case 1, we use (7)-(9) after setting $\hat{\mathbf{h}}_1(\mathbf{s}_i) = \hat{\mathbf{h}}_1$ and $\Phi_1^{-1}(\mathbf{s}_i) = \Phi_1^{-1}$, and calculate $\hat{P}_2 = \hat{\mathbf{h}}_2(\hat{\mathbf{s}}^1)^H \hat{\mathbf{h}}_2(\hat{\mathbf{s}}^1)$ where $\hat{\mathbf{s}}^1$ is the state associated with the smallest metric at time $k=1$.

The hybrid-MLSE reduces to the TD-MLSE where $T_H = 0$ and to the PSP-MLSE when $T_H = \infty$. The threshold T_H should be determined by considering the tradeoff between performance and complexity. The cumulative distribution function (cdf) of the received power P_k should help determine the threshold value. This cdf will be empirically obtained in the next section.

It should be pointed out that the performance of the hybrid-MLSE degrades if the switching between the TD- and PSP-MLSEs occurs too often. To explain this, we consider *Case 1* above. In this case, (4) is evaluated at time $n-1$ for obtaining $\hat{\mathbf{h}}_n$; and (7) is evaluated at time n. Note that at time $n-1$ the sample r_{n-1-D} is applied to (4) and at time n the sample r_n is applied to (7). This indicates that the data between r_{n-1-D} and r_n are ignored due to the switching. This jump in data usage should degrade the channel tracking performance and eventually the receiver performance. In a similar manner, we can argue that the switching of *Case 2* impairs channel tracking and the receiver performance. Since switching between the TD- and PSP-MLSEs occurs more frequently in fast fading channels, the hybrid-MLSE for fast fading channels tends to require larger threshold value than does the one for slow fading channels.

IV. Simulation Results

To examine the performance of the proposed receivers, computer simulations were performed for a TDMA system over frequency-selective Rayleigh fading channels. The modulation scheme was DQPSK with symbol rate 24.3ksymbol/s and 900MHz carrier frequency. The data sequence was arranged into 200 symbol frames, in which the first 20 symbols of each frame was a training sequence. In the simulation, a total of 5000 frames was generated and transmitted through a two-ray Rayleigh fading channel which was modeled as:

$$c(t) = \alpha_0(t)\delta(t) + \alpha_1(t)\delta(t-\tau) \tag{13}$$

where $\alpha_0(t)$ and $\alpha_1(t)$ are independent zero mean complex Gaussian processes and τ is the time delay between the two rays. For simplicity, a normalized uniform delay power profile is assumed, i.e., $E[|\alpha_0(t)|^2] = E[|\alpha_1(t)|^2] = 0.5$ ($E[P_k] = 1$). It was assumed that τ is 2T, which leads to 16-state MLSE receivers ($L = 3$). The behavior of the hybrid-MLSE receivers was examined while varying the vehicle speed from 50km/h to 200km/h. The channel parameters were estimated by the RLS algorithm with the forgetting factor 0.7 (the performance of the hybrid-MLSE was almost invariant for the forgetting factors in between 0.6 and 0.7). For TD-MLSE, several values of decision delay D were tried and the value $D = 2$ exhibiting the best performance

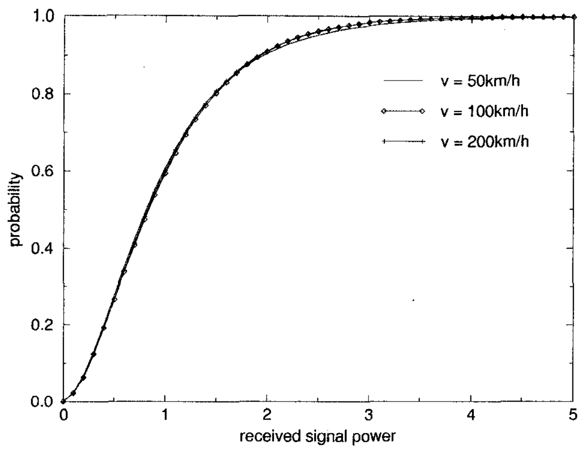


Fig. 2. Empirical cdfs of the received signal power P_k.

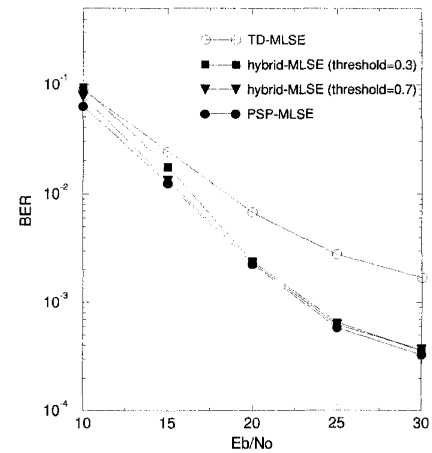
was chosen.

In our experiments, we first evaluated empirical cdfs of P_k under the assumption that the channel $\mathbf{h}_k$ is known. The results for vehicle speeds 50, 100 and 200km/h are shown in Fig. 2. Three cdfs in the figure are almost identical. We can see that the hybrid-MLSE selects the TD- and PSP-MLSEs with almost equal probability when T_H is about 0.8.

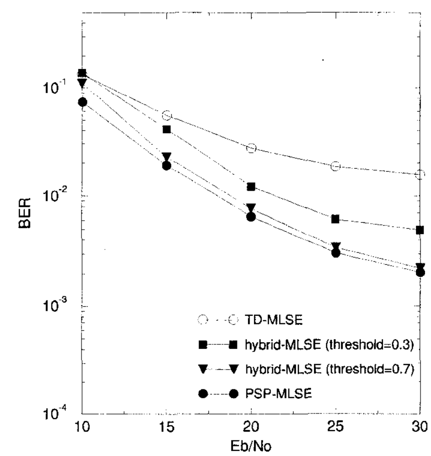
Fig. 3 compares the performance of the TD-, PSP- and hybrid-MLSE algorithms. As expected, the behavior of the hybrid-MLSE improves as the threshold increases. It is interesting to note that the relative performance of the hybrid-MLSE varies with the vehicle speed. For example, comparing the hybrid-MLSE with $T_H = 0.7$ and the PSP-MLSE, the former is comparable to the latter when the vehicle speed is less than 100km/h; however, the former performs considerably worse than the latter for the speed 200km/h. This phenomenon may be ascribed to the switching that occurs more frequently for high speed (Table 1). As the vehicle speed increases, the hybrid-MLSE tends to require a larger T_H.

	v=50km/h	v=100km/h	v=200km/h
$T_H = 0.3$	0.755	1.047	2.182
$T_H = 0.7$	1.189	1.580	3.163

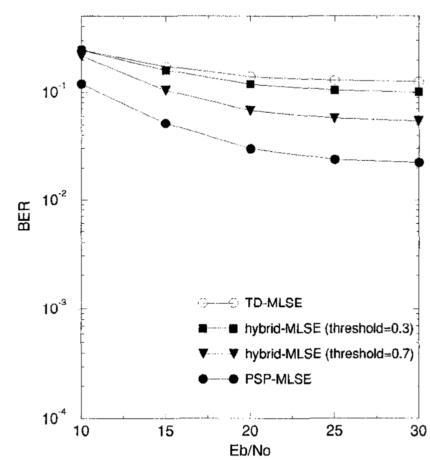
Table 1. Mean value of the number of switchings per frame in the hybrid-MLSE ($E_b/N_o = 20$dB).



(a) v = 50km/h ($f_D T$=0.0017)



(b) v = 100km/h ($f_D T$=0.0034)



(c) v = 200km/h ($f_D T$=0.0068)

Fig. 3. Comparison of BER performance where $f_D T$ is the normalized Dopper frequency.

V. Conclusion

In an attempt to reduce the complexity of the PSP-MLSE, we proposed the hybrid-MLSE that employs both the TD- and PSP-MLSEs and selects either one of them depending on the instantaneous signal power. In the hybrid-MLSE, the signal power estimate is obtained by using channel estimates and compared with a pre-determined threshold T_H. Through computer simulation, a guideline for determining T_H was presented. It has been observed that the hybrid-MLSE for fast fading channels tends to require larger threshold value than does the one for slow fading channels.

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