SEARCH ALGORITHM FOR MLSE-PSP RECEIVERS OVER FAST FREQUENCY-SELECTIVE FADING CHANNELS

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ABSTRACT

In this paper we address adaptive maximum-likelihood sequence estimation using per survivor processing (MLSE-PSP) over fast frequency-selective fading (FFSF) channels. Special care is dedicated to the choice of the search algorithm (SA) used in these schemes and its influence on the receiver symbol error rate (SER) performance, which is evaluated by Monte Carlo simulation. Results of several experiments under conditions of varying signal-to-noise ratio (SNR) and maximum Doppler shift (f_D) are reported. They show that the SA plays a fundamental part in the improvement of the MLSE-PSP reception performance and that the judicious choice of the SA is an effective approach to obtain efficient schemes.

1. INTRODUCTION

Sequence estimation over fast frequency-selective fading (FFSF) channels has been a topic of increasing research interest mainly because of its potential application to mobile communications. It is well known that Maximum Likelihood Sequence Estimation (MLSE) over dispersive and additive white Gaussian noise (AWGN) channels is obtained by minimizing the Euclidean distance between the received sequence and all the possible transmitted ones [1,2]. For a known time-invariant channel MLSE can be efficiently implemented by the Viterbi Algorithm (VA) [3] whose complexity increases exponentially with the channel impulse response (CIR) length. On the other hand, for unknown time-variant channel the MLSE criterion (joint data and Channel estimation) is only implemented by exhaustive search [4] whose computational complexity increases exponentially with the *sequence* length. For this situation various adaptive MLSE schemes with limited complexity have been proposed, among which those employing per survivor processing (PSP) [5-8] have received special attention, in particular for sequence estimation over fast time-varying channels [2].

A MLSE-PSP receiver uses a set of data-aided estimators of channel parameters (a bank of adaptive filters (AF)) embedded into the structure of a search algorithm (SA). The SA supplies the bank of AF with extended surviving sequences to be used for channel parameters estimation. On the other hand, the adaptive filters send back the updated channel parameters which are used for decision metric evaluation.

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The superiority of MLSE-PSP receiver performance over FFSF channels is due to two main reasons [5]. Firstly, there is no delay in the survivors selection, which is a serious impairment in conventional MLSE [1]. Secondly, the MLSE-PSP scheme regards several sequences in the estimation of the unknown channel parameters while the conventional MLSE scheme uses only one sequence (the "best" one). Therefore a MLSE-PSP receiver yields a more accurate approximation to the joint ML estimation of the CIR and symbols.

In spite of having better performance characteristics than other adaptive MLSE schemes, there are several open research topics concerning MLSE-PSP schemes, such as the choice of the AF algorithm and the SA [6]. Although any algorithm can be used to select the sequences to be retained by the receiver (survivors), the Viterbi algorithm (VA) has been adopted frequently [3]. In this case, the receiver uses Q^L adaptive filters, where L is the channel memory length expressed in symbol intervals and Q is the size of the modulation symbol alphabet.

In this work we focus on the selection of the SA for MLSE-PSP schemes employing the LMS algorithm for channel estimation [9]. Computer simulations have been conducted in order to evaluate the SER performance of these schemes considering several values for the number of survivors retained in the search, under different fading conditions.

The remainder of this paper is organized as follows. The system model and our approach to the selection of the search algorithm are described in Section 2. In Section 3 we present the simulation results and our conclusions are summarized in Section 4.

2. THE SEARCH ALGORITHM SELECTION

We assume the baseband-equivalent transmission system model shown in Fig. 1, where $\{I_n\}$ is the transmitted information sequence, $\eta(t)$ is a sample function of a zero-mean complex *additive white Gaussian* process, z(t) is the received signal complex envelope, $\{r_n\}$ is a sequence of signal samples at the baud rate, T is the symbol interval, and $\{\hat{I}_n\}$ is an estimate of $\{I_n\}$. The channel is modeled as Gaussian WSS-US ("Wide Sense Stationary - Uncorrelated Scattering") with equally spaced discrete power delay profile. The channel output is given by

$$y(t) = \sum_{i=0}^{L} h_i(t)\,x(t-iT), \tag{1}$$

where $\{h_i(t),\ i = 0, 1, ..., L\}$ are zero mean independent complex Gaussian processes, and L is the channel memory length. The power spectrum of each channel ray is given by

$$G(f) = \begin{cases} \sigma_i^2 \Big/ \sqrt{1 - \left(f/f_D \right)^2}, & |f| < f_D \\ 0, & |f| > f_D \end{cases} \tag{2}$$

where σ_i^2 is its mean power and f_D is the maximum Doppler shift [10].

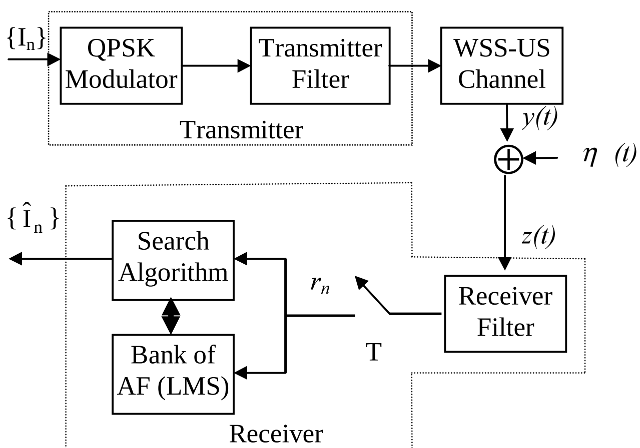


Fig. 1 - Baseband Equivalent Transmission System Model.

The receiver is composed of a receiving filter, a sampler, a search algorithm and a bank of adaptive filters. As no complexity limited search algorithm is able to implement the MLSE criterion over unknown channels [4], a class of good search algorithms to be used in MLSE-PSP receivers is required. In a companion work [11] this theme was exploited considering MLSE-PSP schemes using Kalman filters and second-order autoregresive (AR-2) channel variation modeling. The simulation results in [11] showed that the M-algorithm provides excellent performance, with no floor at the SER curves even when the number of survivors is reduced to 4. We also verified that this scheme exhibits exceptional capacity to track the channel impulse response (CIR) variations.

It is worthy to note that the performance improvements obtained in [11] were partially due to the use of Kalman filtering and AR-2 channel modeling. This topic was further discussed in [12] where an investigation of AF algorithms for MLSE-PSP receivers was addressed.

In this work we intend to accomplish a more exhaustive investigation of the isolated contribution of the SA to the receiver performance improvement. With this aim we fixed the LMS algorithm as the MLSE-PSP filtering strategy, because it is the earliest, the simplest and still the most widely utilized adaptive filtering algorithm. With respect to the SA we propose the use of the Generalized Viterbi Algorithm (GVA) [13]. While the Viterbi algorithm works by taking the survivors from Q^L lists of Q candidates (one survivor per list is chosen), the GVA selects the S (1≤S) "best" survivors in each one of N_L lists of candidates having the same K (K ≤ L) last symbols (N_L=Q^K).

The GVA corresponds in fact to a large class of search algorithms which are defined by the choice of parameters N_L and S. It comprises, for instance, the M-algorithm (N_L=1,S=M) and the VA (N_L=Q^L,S=1). We denote a GVA with parameters N_L and S by GVA(N_L,S). In the particular cases of GVA(Q^L,1) and GVA(1,S) we will use the notations VA and M(S), respectively.

3. SIMULATION RESULTS

We have considered a QPSK modulator (Q=4) at rate 24.3 Kbaud. The transmitter and receiver filters are matched filters with square root raised cosine *impulse response* (IR). We assume perfect receiver clock synchronization, so the inter-symbol interference (ISI) is supposed to result from multipath fading only [1].

The time-varying CIR was imposed to be composed of 4 taps (L=3), T seconds apart, with variances 0.45, 0.3, 0.15 and 0.1. Each tap has been simulated using the Monte Carlo technique presented in [14]. Two values of the maximum Doppler shift (f_D) were considered: 50 and 100 Hz, which correspond to speeds of 60 and 120Km/h, respectively, for a 900 MHz carrier.

The SER performance evaluation was been carried out by Monte Carlo simulation and averaging over 3000 independent runs, each one involving the transmission of 500 symbols (an amount of 1500000 symbols). The noise variance was adjusted in accordance with the SNR at the receiver filter input, expressed by the ratio between the *energy per bit* (E_b) and the noise *Power Spectral Density* (N_0) [1]. The E_b/N_0 ratio was varied from 0 to 30 dB, with 2 dB increment.

As we were only interested in channel tracking, we ignored channel acquisition and assumed perfect training, so the channel estimates were correctly initialized at the beginning of the reception, for each block. With respect to the LMS step-size parameter, we verified by simulation that the value 0.25 yields good tracking characteristics for the range of maximum Doppler shift and SNR considered in this work. This value was used in all the simulations reported in the following. In addition, we have assumed decisions delayed by (5L-1)T. It is well known that for the Viterbi algorithm the decision delay at (5L-1)T is enough to assure a high probability of trellis path merging [3].

Fig. 2 illustrates the SER performance of two SA that retain 4 survivors, namely the M(4)-algorithm and the GVA(1,4), for two values of the maximum Doppler shift (50 Hz and 100 Hz). It is seen that the M(4) algorithm performs better than the GVA(4,1), for both values of the maximum Doppler shift. For instance, at E_b/N_0=25dB and f_D=50Hz the GVA(1,4) produces SER=10^{-1} whereas the M(4) algorithm achieves SER=10^{-2}. Fig. 2 also shows the performance degradation produced by the increase in f_D from 50 to 100 Hz, for both search algorithms.

To further investigate the effect of the SA algorithm on the receiver performance, Figs. 3 and 4 show the SERxE_b/N_0 curves for algorithms that retain 16 and 64, respectively, under transmission conditions similar to those assumed in Fig. 2.

Fig. 3 illustrates the SER performance of the GVA(4,4), the GVA(16,1) and the M(16) algorithm while Fig. 4 depicts the performance produced by the algorithms GVA(16,4), VA, and M(64). Figs. 3 and 4 show clearly that the M-algorithm produces remarkable performance improvement over the other search procedures.

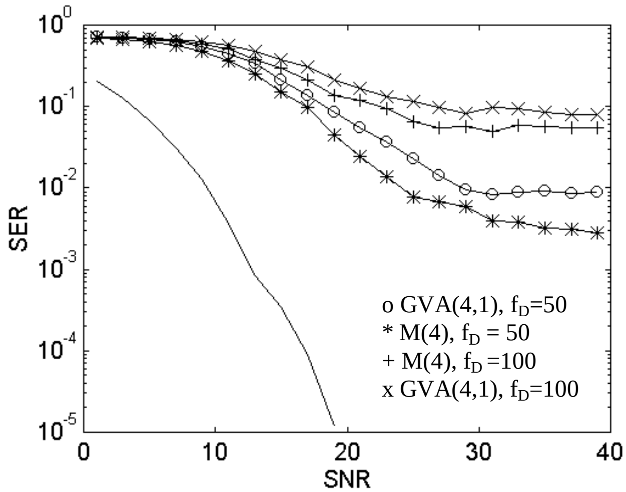


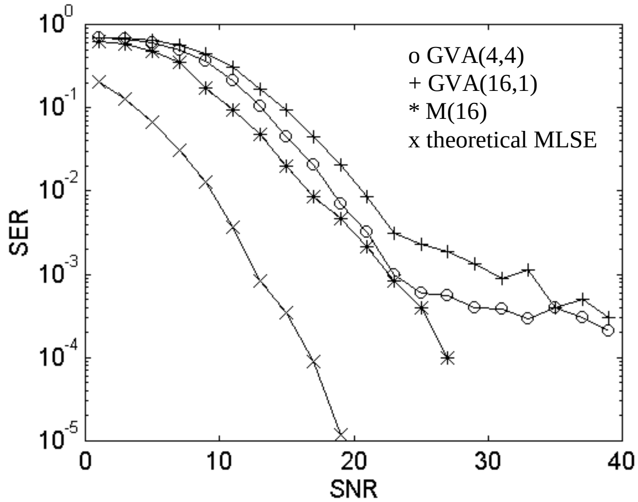
Fig. 2 - SER x SNR for an MLSE-PSP scheme employing SA with 4 survivors.

Comparing the performance results presented in the Figs. 2, 3 and 4 we verify the improvement in the SER performance produced by increasing the amount of survivors. However we may observe in Fig. 4(b) that the VA and the GVA(16,4), in spite of retaining 64 survivors in the search, are unable to eliminate the "irreducible SER" effect when f_D is increased to 100Hz.

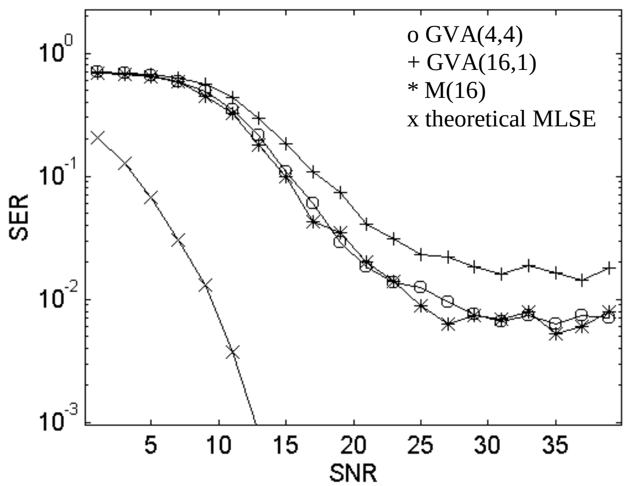
It is worthy to point out that, unlike the other SA evaluated in this work, the M(64)-algorithm did not produce floor at the SER curves when f_D=100Hz.

In order to shed more light on the error generation mechanisms in the MLSE-PSP receivers under study the histogram in Fig. 5 shows the amount of observed errors (in 500 independent trials) in 25 successive intervals (bins) of duration 20Ts, from the beginning to the end of each block, for the M(16) algorithm at E_b/N_0=21dB and f_D=50 Hz. It may be observed in Fig. 5 the increase in the amount of errors as along with the bins.

This effect of error concentration at the end of information block was verified to be caused by CIR tracking loss. This is illustrated in Fig. 6, which shows that MSE (Mean Square Error) in the CIR estimation increases along with the number of received symbols. These characteristics of error concentration and tracking loss were also verified in all other simulation experiments we conducted in this work.



(a) f_D = 50 Hz

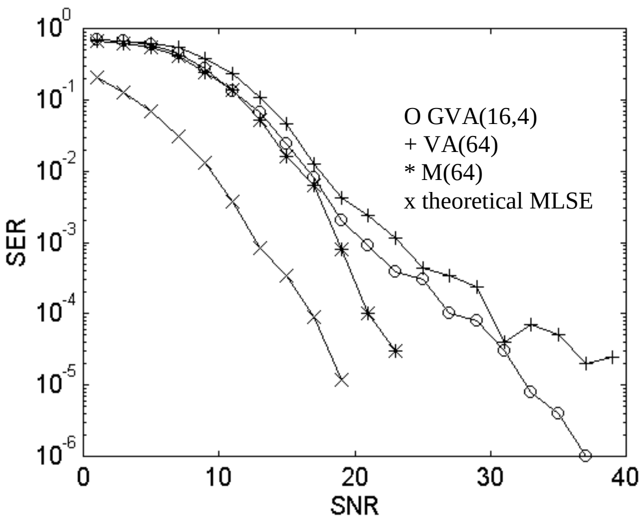


(b) f_D = 100 Hz

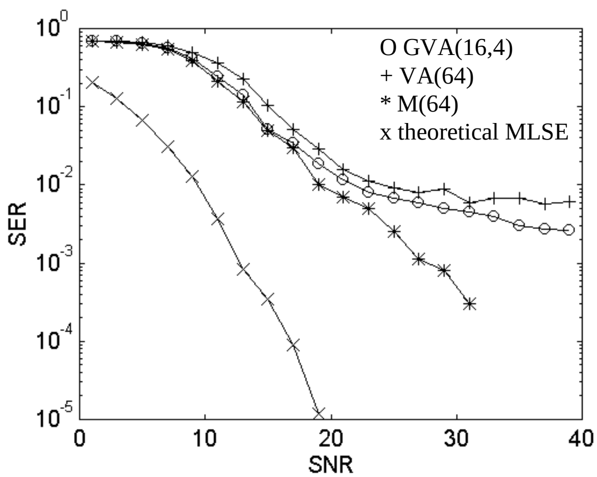
Fig. 3 - SER x SNR for an MLSE-PSP scheme employing SA with 16 survivors: (a) f_D = 50 Hz and (b) f_D = 100 Hz.

In light of these results, we can say that the receiver performance is limited by the LMS tracking errors when the information block length is increased. A very different behavior was observed in [11] where we considered MLSE-PSP schemes using the M algorithm and Kalman filtering with AR-2 channel modeling**.**

After the end of this work the authors have been aware of another paper on the same subject, which come to similar conclusions [15] in respect to the search algorithms for MLSE/PSP receivers. Besides several differences on the assumed transmission environment the present work addresses an in-depth discussion of the error generation mechanism within MLSE-PSP receivers, which is not explicitly considered in [15].



(a) f_D = 50 Hz



(b) f_D = 100 Hz.

Fig. 4 - SER x SNR for an MLSE-PSP scheme employing SA with 64 survivors. (a) f_D = 50 Hz and (b) f_D = 100 Hz.

4. CONCLUSIONS

MLSE-PSP receivers over fast frequency-selective fading channels were investigated in this work. In particular, we focused on schemes using the LMS algorithm for channel estimation, whose performances were evaluated by Monte Carlo simulation. Special attention was dedicated to the choice of the search algorithm.

Our simulation results showed that the M-algorithm is an excellent search procedure for MLSE-PSP receivers and that this algorithm by itself produces significant performance improvement.

We also verified that in spite of playing a fundamental part in the receiver performance, the improvement provided by the M-algorithm is limited by channel tracking errors due to the LMS algorithm, especially when the length of the received information block is increased. In a previously published work [11] we verified that this limitation may be circumvented by using Kalman filtering with AR-2 channel modeling.

From the foregoing performance discussion and that presented in [11] it is apparent that in order to obtain the best performance characteristics of MLSE-PSP over FFSF WSS-US channels it would be necessary the simultaneous use of the M-algorithm and AR-2 Kalman filtering. The only impairment of the schemes so obtained is the increase in computational complexity due to Kalman filtering. In the continuation of this work we intend to investigate the use of AR-2 channel modeling and less computational demanding filtering strategies in order to reduce the complexity of these schemes without sacrificing their performance characteristics. We also intend to evaluate the robustness of these schemes to mismatch in channel modeling.

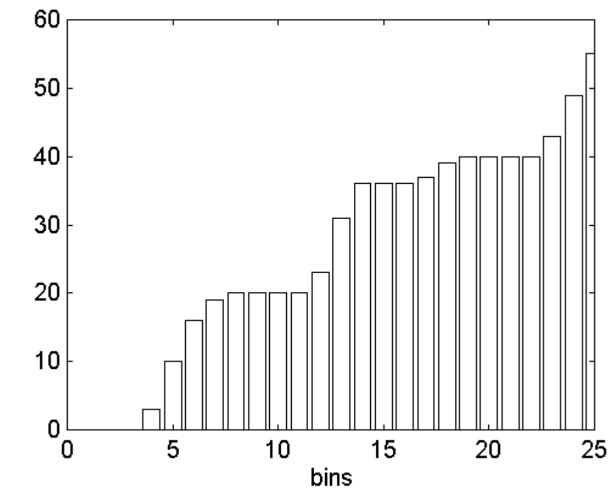


Fig. 5 - Histogram for M(16), f_D=50 Hz and E_b/N_0 = 21 dB.

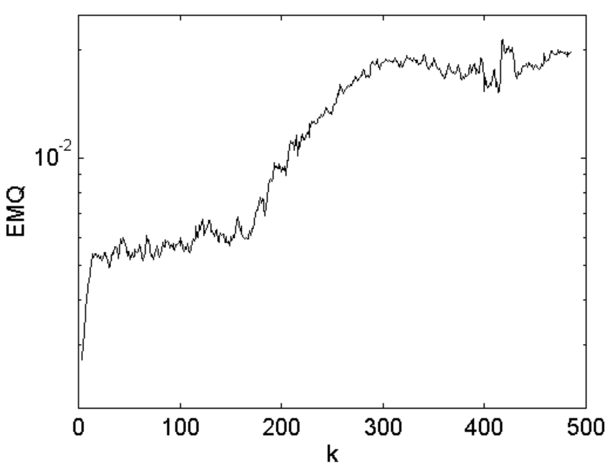


Fig. 6 - MSE for M(16), f_D = 50 Hz and E_b/N_0 = 21dB**.**

4. REFERENCES

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