A Performance Review of PSP for Joint Phase/Frequency and Data Estimation in Future Broadband Satellite Networks

Alessandro Vanelli-Coralli, Member, IEEE, Paola Salmi, Member, IEEE, Stefano Cioni, Student Member, IEEE, Giovanni Emanuele Corazza, Member, IEEE, and Andreas Polydoros, Fellow, IEEE

Abstract—In unknown channels, nonadaptive maximum likelihood sequence detection (NA-MLSD) is far from optimum in the presence of channel-induced uncertainty. To counteract this uncertainty, conventional solutions augment MLSD with external channel estimators. However, for very low SNR values this estimation procedure becomes marginal and the conventional adaptive MLSD (CA-MLSD) approaches perform poorly. We consider joint data decoding and parameter estimation techniques, and in particular per survivor processing (PSP) techniques, as a potentially effective solutions to this problem, at the expense of increased complexity. The performance/complexity tradeoff is addressed in the paper for a convolutionally encoded Q-PSK return link of an SHF/EHF satellite system for multimedia services impaired by phase noise and frequency offsets. By contrasting NA-MLSD, CA-MLSD, and PSP, ranges are provided for channel conditions where the tradeoff favors a particular technique. Further, CA-MLSD and PSP are also contrasted in terms of scalar/vector estimation performance.

Index Terms—Adaptive decoding, frequency estimation, maximum likelihood detection, parameter estimation, per survivor processing, phase estimation, satellite communication, Viterbi detection.

I. INTRODUCTION

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his paper contains a performance/complexity tradeoff for various maximum likelihood sequence detection (MLSD) techniques, namely nonadaptive MLSD (NA-MLSD), conventional adaptive MLSD (CA-MLSD), and per survivor processing (PSP), when applied to the detection of convolutional encoded phase shift keying (PSK) signals for the return link of a multimedia interactive satellite system in the presence of phase/frequency uncertainty.

It is well known that the NA-MLSD approach is the optimum decoding strategy for convolutional encoded signals in completely known channels. However, when channel-induced parameter uncertainty is significant on the received signal, e.g., carrier phase uncertainty, symbol or baud epoch uncertainty, frequency offset, phase noise, or channel-dispersion coefficients, adaptive MLSD (A-MLSD) approaches are necessary [1]–[7].

In CA-MLSD [2], the nuisance parameters embedded in the received waveform are estimated in a segregated way. Accordingly, the CA-MLSD receiver includes parameter estimator (PE) subsystems such as bit synchronizers, automatic gain controllers (AGCs), suppressed-carrier phase lock loops, frequency trackers, and channel equalizers (or estimators) that extract values for the relevant parameters and provide them to the Viterbi Algorithm (VA) to restore approximately additive white Gaussian noise (AWGN) conditions. During PE operations, transmitted data are a nuisance which can be dealt with according to three approaches: nondata-aided, data-aided, and decision feedback (DF). When DF is used in conjunction with VA, the tentative decisions are extracted at a smaller delay than that destined for the actual output, thus trading off decision reliability with estimate timeliness, striving to contain error propagation effects. Unfortunately, the tradeoff becomes more and more difficult in challenging channel conditions, e.g., in low SNRs and fast time variability.

To overcome this drawback, the PSP data decoding/parameter estimation technique has been introduced [3]–[7], stemming from the theory of the generalized likelihood ratio test (GLRT) [8], whereby a separate estimate is obtained for each hypothesized data sequence. Thus, the PSP receiver embeds the estimation into the structure of the search algorithm itself: each survived data sequence in the VA feeds its own PE providing in this way zero-delay localized estimates to each branch metric computation.

Clearly, the advantages of A-MLSD techniques come at the price of a complexity increase, which becomes significant when PSP is considered. This work aims exactly at comparing NA-MLSD, CA-MLSD, and PSP receiver architectures to find out those channel conditions in which this complexity increase is worth the performance improvement.

The focus is placed on coherent reception of a convolutional encoded PSK signal in the presence of phase/frequency uncertainty. As for the application scenario, we consider future multimedia broadband satellite network at EHF/SHF frequencies. Most of these systems have in fact applied for spectrum at K_a and even at V band either in geostationary earth orbit (GEO) or nongeostationary orbits, such as medium earth orbit (MEO) or low earth orbit (LEO) [9]. Some of the link impairments that
must be faced by these systems are frequency offsets due to the Doppler effect and/or oscillator mismatch and phase noise induced by oscillators. Frequency offsets are very large when LEO or MEO satellites are adopted, whereas phase noise is particularly relevant to low data rate transmissions which, due to the asymmetric nature of the multimedia traffic, normally occur in the return link, from the user to the gateway.

Accordingly, in this work a time-varying phase model is considered. The angle disturbance consists of a phase rotation, modeled as a Wiener process, plus a fixed frequency offset. The offset should be intended as the residual offset at the output of an automatic frequency control front-end processor or preamble-based frequency estimator. Due to frequency offsets, we must resort to a second-order closed loop (SOL) approach to track phase variations [10].

In this framework, NA-MLSD and A-MLSD (CA-MLSD and PSP) will first be compared in terms of bit error rate (BER) as a function of the channel conditions to extract performance/complexity tradeoffs. Then, the estimation performance for the A-MLSD will be considered, in terms of mean and standard deviation of the estimation error and of mean time to slip (MTTS, i.e., the number of symbols for which the angle estimation error is within the tracker pull-in range). Since in PSP parameter estimation is distributed over a set of estimators, this analysis is not trivial. To face this problem, we introduce the concepts of “decision-related composite tracker” (DT) and “virtual composite tracker” (VT) and we compare their performance with that of the single external CA-MLSD tracker. In the analysis we benchmark A-MLSD performance with that achievable by the ideal known data (KD) and known phase (KP) approaches. In the former, the PE is provided with correct data by an external genie, whereas in the latter the VA is provided with perfect channel estimates. Finally, packet transmission (as that occurring in multimedia services) requires fast parameter acquisition to avoid loss of the entire packet. To this aim, a preamble of known symbols is usually included at the beginning of each packet. We address the problem of selecting the preamble length and the estimation algorithm, considering the effects on A-MLSD performance.

A good majority of the scientific work on PSP has been concerned with transmission on intersymbol interference channels. Some authors have addressed the issue of MLSD decoding in the presence of phase uncertainty [4]–[7], albeit with significant differences with the approach adopted here. In [4], a constant phase rotation is assumed and vector tracker-based ML decoding is compared with a first-order loop (FOL) PSP approach. In [5], the phase rotation is modeled as a Wiener process, but no frequency offsets are considered. Thus, an FOL is used in a PSP configuration. In [6], frequency uncertainty is also considered but a noncoherent reception scheme is adopted. In [7], the PSP approach is used for the detection of trellis-coded modulation with reference to similar channel conditions. However, our work differs by dwelling into estimation performance analysis, including MTTS evaluation, and into a detailed study for preamble design. In addition, detection performance is assessed over a wider range of channel conditions, to allow significant tradeoffs.

II. SYSTEM MODEL AND METRIC COMPUTATION

In the system under consideration the information bit sequence \( \{b_k\} \) is encoded into the symbol sequence \( \{v_n\} \), by way of a rate 1/2, constraint length \( L = 7 \) convolutional code, and then fed to a Q-PSK mapper. Letting the encoder state at time \( k \) be \( \mu_k = (b_{k-1}, b_{k-2}, \ldots, b_{k-L+1}) \) and denoting the state transition as \( \mu_k \rightarrow \mu_{k+1} \), the Q-PSK symbol corresponding to the state transition \( \mu_k \rightarrow \mu_{k+1} \) is represented as \( \alpha_k = \alpha(\mu_k \rightarrow \mu_{k+1}) \). The complex Q-PSK symbol sequence \( \{\alpha_k\} \), with average energy per symbol \( E_s = E(\{\alpha_k\}^2) \), where \( E(\cdot) \) denotes statistical expectation, is formatted into packets of \( N_{\text{symb}} \) symbols. At the beginning of each packet a preamble of \( N_{\text{preamble}} \) known symbols may be included to ease initial parameter acquisition in the receiver section.

Assuming negligible filter distortion, symbol rate sampling, and perfect symbol timing recovery in the receiver, the complex samples at the output of the matched filter feeding the VA decoder can be expressed as

\[
r_k = \alpha_k e^{j\theta_k} + w_k
\]

where \( w_k \) is a circularly symmetric complex AWGN process whose independent quadrature component samples have identical variance equal to \( N_0/2 \) and \( \theta_k \) is the phase rotation

\[
\theta_k = 2\pi \Delta f T k + \phi_k.
\]

In the above equation, \( \Delta f T \) represents the residual carrier frequency offset, due to Doppler effect, normalized to the symbol rate and \( \phi_k \) accounts for the phase noise introduced by the fluctuations in signal source and local oscillators within the transmitter, satellite transponder, and receiver. The frequency offset \( \Delta f T \) is assumed to be deterministic and constant during the transmission of each packet, whereas the phase sequence \( \{\phi_k\} \) is modeled as a Wiener random process characterized by zero mean Gaussian independent increments with standard deviation \( \sigma_{\phi'} \).

This discrete-time phase noise process represents a sampled (at the symbol rate) version of a continuous-time phase noise process \( \phi(t) \), whose corresponding model is that of a classic continuous-time (CT), zero-mean Wiener–Levy process (or Brownian motion). The variance of this nonstationary CT process is proportional to the time index, \( E[\phi^2(t)] = 4\pi/3 \beta t [\text{rad}^2] \), where \( \beta \) is the one-sided 3-dB bandwidth (linewidth) of the power spectrum of the related complex-envelope process \( \phi(t) \), which can readily be shown to be wide-sense stationary, with an exponentially decaying correlation function and a corresponding Lorentzian power spectrum [12]–[14]. To relate \( \beta \) (and thus, the phase-noise-induced spectral width) to the variance of the sampled process introduced above, we note that due to the independent increment property of the Wiener–Levy process, \( E[\phi(t + \tau) - \phi(t)]^2 = 4\pi/3 \beta \tau \). Hence, assuming that filtering effects are negligible, which is reasonable for the cases considered in this paper, and sampling the CT process at symbol intervals apart yields \( \sigma_{\phi}^2 = 4\pi/3 \beta R = 4\pi/3 R \text{ [rad}^2] \), where \( R \) is the data rate. We note that the CT Wiener model is

\[1\]Note that although strictly speaking in the presence of frequency errors a different front-end should be used, this approach is usually followed for residual frequency errors up to 10%–20% of the symbol rate [11].
the one and only fully statistical model found in the literature, with a dearth of other sample-path models, hence is the one adopted here despite some theoretical and practical questions lingering with respect to its connection with phase-noise spectra measured in practice.

At each discrete time instant $k$ the VA updates the path metrics by performing the classical add–compare–select (ACS) operation. In particular, let

$$\lambda(\mu_k \rightarrow \mu_{k+1}) = F[\alpha_k, r_k, \hat{\theta}_k]$$  \hspace{1cm} (3)

be the branch metric pertaining to the transition $\mu_k \rightarrow \mu_{k+1}$ at discrete time $k$. $F[\cdot]$ represents the metric functional dependence on the Q-PSK symbol corresponding to the state transition, on the received sample, and on the channel phase estimate $\hat{\theta}_k$. The accumulated metric at discrete time $k + 1$ turns out to be

$$\Gamma(\mu_{k+1}) = \min_{\mu_k} [\Gamma(\mu_k) + \lambda(\mu_k \rightarrow \mu_{k+1})].$$  \hspace{1cm} (4)

In the following we will denote with $\mu_k$ the state that survives the ACS operation, i.e., the state that minimizes (4).

Finally, a decision is taken at each symbol period by truncating the VA at a depth of $D$ Q-PSK symbols, i.e., at each symbol period the best (minimum) metric state is chosen and the symbol found by moving $D$ steps backward along the path leading to this state is decoded. Note that the various decoding approaches differ in the way they compute the phase estimate $\hat{\theta}_k$ and how they use it in (3).

III. NONADAPTIVE MLSD

In the NA-MLSD approach, no phase tracking is performed (however, ideal phase acquisition is assumed). In this case, the branch metric is simply

$$\lambda(\mu_k \rightarrow \mu_{k+1}) = |r_k - \alpha(\mu_k \rightarrow \mu_{k+1})|^2. $$  \hspace{1cm} (5)

In Fig. 1 the BER for NA-MLSD is reported as a function of the frequency offset, $\Delta fT$, for phase noise standard deviation $\sigma_\phi \in \{0^\circ, 0.3^\circ, 1^\circ, 3^\circ, 5^\circ\}$, $E_b/N_0 = 3$ dB, $E_b$ being the received energy per bit, and, as for the rest of the paper, $N_{\text{symb}} = 150$ Q-PSK symbols. Along with the BER curves, the ideal performance achievable by the ideal KP reference scheme is reported (thick line) for comparison. By inspection of this figure the following considerations can be drawn. First, looking at the curves for $\sigma_\phi = 0$, we can argue that the frequency offset effects remain negligible up to $\Delta fT \leq 10^{-4}$. On the other hand, above $\Delta fT = 10^{-3}$ performance is totally degraded. Therefore, there is a steep region of transition from satisfactory to unsatisfactory performance in the range $10^{-4} < \Delta fT < 10^{-3}$. Second, fixing a low frequency offset such that no degradations can be ascribed to it (i.e., $\Delta fT \leq 10^{-4}$), we can observe that the phase noise produces an unacceptable BER floor whenever its standard deviation $\sigma_\phi$ becomes greater than one degree; for lower values performance degradations can be considered to be negligible. In summary, whenever the system model is such that $\sigma_\phi > 1^\circ$ and/or $\Delta fT > 10^{-4}$ the use of an adaptive scheme is mandatory to achieve satisfactory performance.

IV. ADAPTIVE MLSD

In the A-MLSD approach, channel parameter estimates are used in the branch metric computation in the attempt to equalize the channel-induced phase rotation, i.e., given the phase estimate $\hat{\theta}_k$ the branch metric is computed as

$$\lambda(\mu_k \rightarrow \mu_{k+1}) = |r_k e^{-j\hat{\theta}_k} - \alpha(\mu_k \rightarrow \mu_{k+1})|^2. $$  \hspace{1cm} (6)

As previously mentioned, due to the frequency error induced by the Doppler effect, the phase estimation is performed by an SOL tracker, used either in a single external (CA-MLSD) or in a distributed (PSP) configuration. The SOL equations are [10],

$$\hat{\theta}_{k+1} = \hat{\theta}_k + \xi_k$$ \hspace{1cm} (7)

and

$$\xi_k = \xi_{k-1} + \gamma(\beta c_k - c_{k-1})$$ \hspace{1cm} (8)

where $\xi_k$ and $c_k$ are the radial frequency error and the error signal at time $k$, and $\gamma$ and $\beta$ are the loop parameters, respectively. Ideally, the SOL error signal would be computed as

$$c_k = \text{Im}\left\{ r_k e^{j\hat{\theta}_k} \right\}. $$ \hspace{1cm} (9)
However, in A-MLSD, $\alpha_k$ in (9) must be replaced with its estimate. Unfortunately, in the VA a decision is taken with a delay of $D$ symbol periods, essentially preventing its use in the error signal computation. In fact, due to the channel time-varying characteristics the decoded data are obsolete with respect to the present channel state. As we will show in the next sections, CA-MLSD and PSP differ exactly in the way they tackle this problem.

A. Conventional Adaptive MLSD

In CA-MLSD, the data symbol $\alpha_k$ in the error signal computation is replaced with a low delay tentative data decision. In other words, instead of tracing back the currently best path for many steps in search of a very reliable data estimate, only a few steps are traced back in search for a more recent but less reliable data estimate. Letting $d$ denote the number of steps traced back, then, at time $k$, the most recent phase and radial frequency estimates available are $\hat{\theta}_{k-d}$ and $\hat{\xi}_{k-d}$. Thus, the branch metric in the CA-MLSD must be computed as

$$\Lambda(\mu_k \rightarrow \mu_{k+1}) = \left| r_k e^{-j(\hat{\theta}_k - \alpha_k \theta_0)} - \alpha(\mu_k \rightarrow \mu_{k+1}) \right|^2$$  

(10)

where the term $\hat{\xi}_{k-d} \theta_0$ provides phase unwrapping, i.e., the projection of the radial frequency error estimate to the present time instant. The value for $d$ drives the tradeoff between the reliability of data aiding and loop response to rapid phase changes.

B. Per Survivor Processing

In PSP, each survived data sequence in the trellis produces its own parameter estimate, i.e., as many SOLs as survivors in the trellis are run in parallel. Note that in PSP no tentative decision must be taken since every hypothesized data sequence generates an estimate, and thus each estimate is perfectly time aligned with the channel samples. Letting $\hat{\theta}(\mu_k)$ be the phase estimate associated to the survivor path ending up at state $\mu_k$, (3) becomes here

$$\Lambda(\mu_k \rightarrow \mu_{k+1}) = \left| r_k e^{-j(\hat{\theta}(\mu_k))} - \alpha(\mu_k \rightarrow \mu_{k+1}) \right|^2.$$  

(11)

The dependence on the survivor path modifies the SOL equations as follows:

$$\hat{\theta}(\mu_{k+1}) = \hat{\theta}(\mu_k) + \xi(\mu_k)$$  

(12)

$$\xi(\mu_{k+1}) = \xi(\mu_k) + \gamma \left[ \hat{\xi}(\mu_k) - \epsilon(\mu_{k-1}) \right]$$  

(13)

whereas the error signal is

$$\epsilon(\mu_k) = I_{\text{ph}} \left\{ r_k e^{j\hat{\theta}(\mu_k)} \rightarrow \mu_{k+1} \right\}. $$  

(14)

Note that the two branch metrics associated to the transitions leading to state $\mu_{k+1}$ are computed using not only different data symbols but also different phase estimates. In fact, $\hat{\theta}(\mu_k)$ in (11) depends on the starting state of the transition $\mu_k \rightarrow \mu_{k+1}$. In other words, SOL equations are updated only after the ACS algorithm has determined the survivor state $\hat{\theta}(\mu_k)$.  

$^2$A different approach is possible by updating the estimate before ACS, leading to a small performance improvement and a doubling of estimation complexity [15].

Finally, it is worthwhile underlining that if the correct data path is present among the survivors then there will be a tracker that will enjoy zero-delay correct data, thus performing as an ideal data-aided scheme would. This advantage must be traded off against the implementation complexity increase.

C. Tracking Loop Initialization

SOL is a recursive scheme that needs to be initialized. By inspection of (7) and (8) and (12) and (13), it is apparent that at starting time $k = 1$ the SOL parameters that must be known are the initial angle phase $\theta_0$ and the initial radial frequency $\xi_0$. In particular, in packet mode such knowledge is required at the beginning of each packet. To this aim, a preamble of known symbols is usually included to ease initial parameter acquisition, at the expense of an increase in the transmission overhead. To investigate the impact in terms of both complexity and achievable system performance of initial parameter acquisition, two different approaches will be considered, namely the genie-aided acquisition and the preamble-aided acquisition approach.

Genie-Aided Acquisition: In this case we bypass the problem of initial phase and frequency estimation. We assume that a genie gives us ideal acquisition on one parameter and a fixed offset on the other. Accordingly, in one case, we assume ideal phase initialization and we let the tracking loop deal with the corresponding frequency uncertainty. In the other case we assume ideal frequency recovery letting the tracking loop deal with the corresponding phase uncertainty. This allows the evaluation of the sensitivity to initial errors on either of the two parameters regardless of the specific estimator architecture.

Preamble-Aided Acquisition: In this case, a short preamble of $N_{\text{pre}}$ known symbols is employed to aid initial acquisition. Since the preamble must be included at the beginning of each data packet, its length must strike a balance between acquisition performance and overhead.

As far as frequency estimation is concerned the theoretical minimum length of a preamble can be directly derived from the modified Cramer–Rao bound (MCRB) [10] as a function of the desired error variance. Letting $\Delta f_T$ be the frequency estimate and $\epsilon_{\Delta f_T} = (\Delta f_T - \Delta f_T)$ the estimate error, the MCRB is

$$\text{Var}\{\epsilon_{\Delta f_T}\} \geq \frac{3(\Omega_\Delta/N_0)^{-1}}{2\pi^2 N_{\text{pre}}^3}. $$  

(15)

Solving for $N_{\text{pre}}$ yields

$$N_{\text{pre}} \geq \left[ \frac{3(\Omega_\Delta/N_0)^{-1}}{2\pi^2 \text{Var}\{\epsilon_{\Delta f_T}\}} \right]^{1/3}. $$  

(16)

By straightforward application of this equation it turns out that, for example, at $\Omega_\Delta/N_0 = 4$ dB a residual frequency offset on the order of $10^{-2}$ can be achieved with a short preamble of around ten symbols; a few tens up to a hundred symbols are needed to limit the residual frequency offsets in the range $[10^{-3}, 10^{-2}]$, while preamble lengths on the order of one to two hundred symbols must be used for target residual frequency offsets in the range $[10^{-4}, 10^{-3}]$.

To be specific, we adopted two preamble lengths: a short preamble of $N_{\text{pre}} = 12$ that allows to limit the overhead to a
few percent of the packet length, at the expense of a minimum achievable error standard deviation on the order of $10^{-2}$, and a longer preamble of $N_{\text{preamble}} = 64$, that achieves smaller error standard deviation with larger overhead. As far as the estimation technique is concerned several data-aided frequency estimation algorithms have appeared in the literature [11]. Among these we selected the Luise and Reggiannini (L&R) algorithm and the Rife–Boorstyn (R&B) algorithm. When the short preamble is used, the L&R algorithm offers a good tradeoff between error standard deviation and unbiased estimation range. Unfortunately, when the preamble length is increased, the unbiased range reduces to become quite unusable. For long preambles we adopted the R&B algorithm, which albeit more complex than the L&R, provides a wider unbiased range (i.e., $\Delta f_T \in [-0.5, 0.5]$) with comparable error standard deviation.

Let $z(k) = r_k\alpha_k^2$, $k = 0, 1, \ldots, N_{\text{preamble}} - 1$ and $R(m) = 1/(N_{\text{preamble}} - m) \sum_{k=0}^{N_{\text{preamble}}-1} z(k)\alpha_k^2$, $1 \leq m \leq N_{\text{preamble}} - 1$. The L&R estimate of $\Delta f_T$ is computed as

$$\hat{\Delta f_T} = \frac{1}{\pi(N_{\text{preamble}}/2 + 1)} \arg \sum_{m=1}^{N_{\text{preamble}}/2} R(m),$$

(17)

The R&B estimate of $\Delta f_T$ is given by

$$\hat{\Delta f_T} = \arg \max_f \left\{ \frac{1}{N_{\text{preamble}}} \sum_{k=0}^{N_{\text{preamble}}-1} z(k)e^{-j2\pi kfT} \right\}.$$  

(18)

The frequency estimate is then used to derotate all the received preamble symbols, and an ML phase estimator is applied. Therefore, an initial phase estimate is obtained as follows:

$$\hat{\theta} = \arg \sum_{k=0}^{N_{\text{preamble}}-1} r_k\alpha_k^2 e^{-j2\pi k\hat{\Delta f_T}}.$$  

(19)

According to this approach, the SOL initial conditions are $\xi_0 = 2\pi \hat{\Delta f_T}(N_{\text{preamble}} - 1)$, $\hat{\theta}_0 = \hat{\theta}$, and $\hat{\theta}_1 = \hat{\theta}_0 + \xi_0$.

V. A-MLSD DETECTION PERFORMANCE ANALYSIS

In this section, simulation results are presented to compare detection performance of the A-MLSD schemes. In all simulation examples, if not stated differently, the depth selected for truncating the Viterbi algorithm, $D$, has been set to 30 Q-PSK symbol periods, i.e., $D = 5 \times (L - 1)$, and the packet length is $N_{\text{symb}} = 130$ Q-PSK symbols. The delay $d$ for the tentative decisions has been set to 1 Q-PSK symbol, as a result of a thorough optimization campaign.

In all cases, the loop parameters, $\gamma$ and $\beta$, have been optimized to minimize BER. The same loop parameter values are also used for estimation performance evaluation. Note that the parameters have been separately optimized for each value of $E_b/N_0$ and for each channel condition as exemplified by the values of the frequency offset $\Delta f_T$ and of the phase noise standard deviation $\sigma_\phi$. This is fair assuming that the link budget of interest is known beforehand.

A. A-MLSD Detection Performance: Genie-Aided Acquisition

Here we report on the performance results for the A-MLSD schemes in the genie-aided approach previously defined. The objective of this section is threefold: to assess the range of parameter values for which the increasing complexity due to the tracking subsystem in the A-MLSD is worth the performance gain with respect to NA-MLSD; to contrast CA-MLSD and PSP performance to highlight the channel conditions for which the CA-MLSD becomes inadequate, while PSP maintains acceptable performance; to provide a design tool for the choice of the preamble length and of the frequency acquisition algorithm. In fact, as we will demonstrate later on, results presented in this section allow us to predict the performance of an A-MLSD system, once the residual frequency offset error is known. On the other hand, when the target BER performance is given, a constraint on the maximum allowable residual frequency offset can be deduced, and thus the frequency acquisition algorithm and the preamble length can be selected to meet this constraint.

As in Section III, we start by reporting in Fig. 2 the BER performance for the A-MLSD (i.e., CA-MLSD and PSP) algorithms as a function of the frequency offset, $\Delta f_T$; for phase noise standard deviation $\sigma_\phi \in \{0^\circ, 0.3^\circ, 1.0^\circ, 3.0^\circ, 5.0^\circ\}$, and $E_b/N_0 = 3$ dB. Again, the ideal performance achievable by the KP reference scheme is reported (thick line) for comparison. Several interesting points can be observed. First, CA-MLSD performance degradation (dashed curves) is slower than for NA-MLSD with increasing frequency offset and phase noise. For example, for $\Delta f_T = 10^{-3}$, and $\sigma_\phi \leq 1^\circ$, BER is on the order of $5 \times 10^{-3}$ for the CA-MLSD (Fig. 2) and on the order of $2 \times 10^{-4}$ for NA-MLSD (Fig. 1). Nevertheless, larger frequency offsets or phase noise standard deviations induce unacceptable performance degradations also for the CA-MLSD. For $\Delta f_T \geq 7 \times 10^{-3}$ CA-MLSD BER crosses $10^{-4}$ independently of the phase noise.

It is worthwhile noting that simulation results performed for different SNR values [15], [17], not reported here for brevity, yielded similar results. Again, for higher SNR this behavior is more apparent, whereas for lower SNR the KP bound will rise and differences between the various approaches become therefore smaller.

The use of PSP techniques adds further significant performance improvements. Each PSP curve (solid) outperforms the corresponding CA-MLSD one. PSP curves keep close to the KP bound longer than the CA-MLSD ones and, therefore, performance degradation is slower. This is well evidenced considering again $\Delta f_T = 10^{-3}$, and for $\sigma_\phi \leq 1^\circ$: BER for PSP is on the order of $9 \times 10^{-4}$ and crosses $10^{-3}$ only for $\Delta f_T > 3 \times 10^{-2}$ for any phase noise standard deviation. It is worthwhile noting that PSP is more robust against phase noise. In fact, PSP curves for different $\sigma_\phi$ are less spread then those for CA-MLSD. The maximum BER difference between curves without phase noise ($\sigma_\phi = 0$) and curves with severe phase noise ($\sigma_\phi = 5^\circ$) is limited to one order of magnitude for PSP, whereas it is almost doubled for CA-MLSD, not to mention NA-MLSD for which this difference amounts to four orders of magnitude. Finally, PSP may outperform CA-MLSD even in significantly worse channel conditions as it is exemplified at $\Delta f_T = 10^{-3}$, and $\sigma_\phi = 3^\circ$. 

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for which PSP achieves a BER ≈ 1 × 10⁻³, while CA-MLSD does not go below 4 × 10⁻³, however small the phase noise standard deviation may be.

In Table I we collect the above considerations in a structured way to give a tool to select the best approach, among the considered ones, for the different channel conditions. To select the best it is necessary to define the criterion for optimality. For our purposes the best approach is the one with satisfactory performance (i.e., BER at least in one order of magnitude from the KP bound) and with the least complexity. Due to the previous consideration about behavior under different SNRs, the case of \( E_b/N_0 = 3 \) dB is taken as a reference. The following observations can be drawn.

For \( \Delta f/T \leq 10^{-4} \) and \( \sigma_\phi < 1^\circ \), all the approaches perform very close to the KP bound; thus NA-MLSD should be considered as the best choice for its simplicity. For any other parameter combination the NA-MLSD has very poor performance and only an adaptive approach should be considered. For \( 10^{-4} < \Delta f/T \leq 10^{-3} \) and \( \sigma_\phi < 1^\circ \), both CA-MLSD and PSP achieve satisfactory performance. Since CA-MLSD is simpler it should be considered as the best choice. Unfortunately, for higher phase noise or frequency offset CA-MLSD is deficient and a more complex approach should be used. For \( 10^{-3} < \Delta f/T \leq 10^{-2} \) or \( \sigma_\phi > 1^\circ \) only PSP can be considered to have satisfactory performance, and thus it represents the best choice. For \( \Delta f/T > 10^{-2} \) none of the SOL-based approaches achieve satisfactory performance. To tackle large frequency offsets, a third-order tracking loop may be used.

As far as the effects of phase initialization errors are concerned, in Fig. 3 the BER performance for the A-MLSD algorithms is reported as a function of the initial phase uncertainty, for phase noise standard deviation \( \sigma_\phi \in \{0^\circ, 0.5^\circ, 1.0^\circ, 3.0^\circ, 5.0^\circ\} \) and \( E_b/N_0 = 3 \) dB. Perfect initial frequency acquisition is assumed. Also in this case it is apparent that each PSP curve outperforms the corresponding CA-MLSD one.

### B. A-MLSD Detection Performance: Preamble-Aided Acquisition

In this section we report on performance results for the A-MLSD schemes in the preamble-aided acquisition approach defined above. The objective of this section is twofold: to show how it is possible to obtain good performance also in case of large phase/frequency uncertainty and to show that the results of the previous section can be used to predict what the performance of an A-MLSD system will be, once the residual frequency offset error is known.

In Fig. 4 BER performance for PSP and CA-MLSD is reported as a function of \( \Delta f/T \), for \( \Delta f/T = 0.01 \) and \( \sigma_\phi = 0.3^\circ \). The KP and KD curves are reported for comparison. It can be observed that PSP performs significantly better than CA-MLSD. For example, at BER = 10⁻³ the gain for PSP is on the order of 2.5–3 dB. The gain gets larger for lower BER objectives. Moreover, the loss of PSP with respect to the KD and KP curves is, respectively, 0.9 dB and 1.4 dB at BER = 10⁻³. This is a good result since in such low \( E_b/N_0 \) conditions channel estimation is generally poor (as testified by the CA-MLSD performance). Similar results have been obtained for \( \Delta f/T = 0.1 \), and \( \sigma_\phi = 0.3^\circ \), although, in this condition, some degradation is visible. This
can be mainly ascribed to the preamble-based acquisition that gets somewhat marginal at $\Delta fT = 0.1$, as clarified by the result of Fig. 6, in which the average frequency offset estimate and frequency error standard deviation of the L&R algorithm are reported for $E_b/N_0 = 3$ dB. However, it is worth noting that the degradation for CA-MLSD is by far larger than for PSP, testifying the robustness of the latter scheme. Fig. 5 shows similar comparisons for $\Delta fT = 0.001$, $\sigma_\phi = 0.3$. Note that the BER are comparable to that of $\Delta fT = 0.01$. This behavior is not unexpected. As a matter of fact, the error standard deviation yielded by the L&R algorithm ($\approx 10^{-2}$) leads the PSP SOL to start from the same initial point experienced for $\Delta fT = 0.01$.

Finally, in Fig. 7 for the sake of completeness we report the BER achievable, for different frequency offset and phase noise standard deviation, by the PSP approach when using a long preamble, $N_{\text{trc}} = 64$, and the R&B estimator. As expected, performance sensibly improves due to the smaller residual frequency offset. For large phase noise standard deviation (e.g., $\sigma_\phi = 5^\circ$) the evident degradation is completely chargeable to the accuracy reduction of frequency estimation as described in Fig. 8.

To further characterize the PSP approach, the percentage of time in which a symbol error occurs in the truncated Viterbi algorithm decision process while at the same time the correct path is present inside the trellis has been evaluated as a function of $E_b/N_0$. This percentage turns out to be around 90% over the full range of $E_b/N_0$ values of interest suggesting that there exists one tracker, inside the distributed PSP tracking structure, that is enjoying correct decisions even when wrong symbols are selected and this is in essence the power of PSP.

We conclude this discussion with the following heuristic proposition:

"the performance achieved by the SOL-based A-MLSD schemes with preamble-based frequency acquisition, yielding residual frequency offset standard deviation $\sigma_\Delta fT$, is equivalent (with good approximation) to
the performance achieved with fixed frequency offset \((\Delta fT)_{\text{fix}} = \sigma_{\Delta fT}\) and no preamble acquisition.

Let us justify the proposition with a couple of examples. In Fig. 5 for\( E_b/N_0 = 3\) dB, and using the L&R estimator with \(N_{\text{pre}} = 12\), PSP and CA-MLSD achieve BER on the order of \(2 \times 10^{-2}\) and \(2 \times 10^{-1}\), respectively. At the same time, Fig. 6 tells us that in this working condition the L&R estimator provides an unbiased estimation with a residual frequency offset \(\sigma_{\Delta fT}\) on the order of \(8 \times 10^{-3}\). Finally, using \((\Delta fT)_{\text{fix}} = \sigma_{\Delta fT}\) in Fig. 2 we obtain a BER slightly larger than \(1 \times 10^{-2}\) for PSP, and \(1 \times 10^{-1}\) for CA-MLSD, which can be considered as a good performance prediction. In Fig. 7 for \(E_b/N_0 = 3\) dB, \(\Delta fT = 0\), and \(\sigma_\phi = 0.3^\circ\) the PSP approach using the R&B estimator with \(N_{\text{pre}} = 64\) achieves BER on the order of \(10^{-3}\). In the same working conditions, the R&B estimator yields \(\sigma_{\Delta fT}\) on the order of \(6 \times 10^{-1}\) (Fig. 8). Thus, using \((\Delta fT)_{\text{fix}} = \sigma_{\Delta fT}\) in Fig. 2 BER turns out to be slightly lower than \(10^{-3}\).

VI. A-MLSD ESTIMATION PERFORMANCE ANALYSIS

As anticipated in Section I, the problem of measuring the estimation performance for a PSP-based scheme is far from being trivial. Essentially the difficulty arises from the fact that multiple SOL estimators are run in parallel, and a poor performance of a (large) subset of them does not necessarily correspond to a poor performance of the algorithm. The approach that has been selected here is the following: at each decoding step the maximum metric path is selected, and the estimator associated to the decoded symbol (i.e., \(D\) steps back from the current time instant) on this winning survivor path is observed. Its estimated angle rotation is subtracted to the actual channel rotation, obtaining an
estimation error sample. Note that the sequence of estimation error samples does not necessarily pertain to any real estimator, because, due to truncation, the winning path will change over time and observation may jump from one estimator to another. We identify this overall “decision-related” composite tracker as DT. As a numerical benchmark to DT, we have introduced the notion of a virtual tracker (VT). VT consists of the collection of the instantaneous best channel estimator, i.e., that which yields the smallest instantaneous estimation error. Obviously, as the adjective virtual suggests, VT is not feasible since it needs a genie telling which among the \(2^L-1\) computed phase estimates is the best one.

Figs. 9 and 10 contain the mean and standard deviation of the SOL estimation error for CA-MLSD and PSP as a function of \(E_b/N_0\) for \(\Delta fT = 0.01\) and \(\sigma_\phi = 0.3^\circ\). For PSP, both the DT and VT tracker performance is shown. Again the KD curve is reported for comparison. All the trackers appear to be unbiased within a fraction of a degree, except for CA-MLSD. In this case the bias is due to the phase difference between the tentative data decision and the actual data caused by the nonideal frequency compensation. The error standard deviation for the PSP DT scheme is almost identical to that of the KD scheme. Note that, except for PSP VT, every scheme yields rather large standard deviations, on the order of 15° at \(E_b/N_0 = 0\) dB, down to 10° at \(E_b/N_0 = 4\) dB. This surprising behavior can be interpreted observing that in a channel with high dynamics due to a Wiener phase noise and a frequency error, it is good to have a large loop bandwidth for tracking purposes. However, in the low \(E_b/N_0\) range of interest to us, this large loop bandwidth degrades the estimation quality. The optimization of the loop parameters with a minimum BER objective seems to have led us into the condition of having the largest possible loop bandwidth which at the same time guarantees in-lock loop stability.

In Fig. 11, the phase estimation error standard deviation is reported for PSP VT and PSP DT schemes as a function of the
decoding delay. In this case, the VT is not evaluated instantaneously but is time-aligned with the DT. Therefore, the VT corresponds to the tracker with minimum phase estimation error. The figure highlights that the longer the decoding delay, the more DT performance gets closer to VT one. In Fig. 11 we also report KD phase estimation error standard deviation for comparison.

Finally, in Fig. 12 we report the MTTS (i.e., the number of symbols for which the angle estimation error is within the tracker pull-in range) performance of the SOL trackers for CA-MLSD and PSP (both DT and VT). The KD MTTS performance is shown for comparison. MTTS is reported as a function of $E_b/N_0$ for $\Delta f T = 0.01$, and $\sigma_\phi = 0.3^\circ$. As expected, the ideal KD MTTS curve outperforms all other approaches. Anyway, DT PSP tracker shows better performance than the CA-MLSD tracker.

VII. CONCLUSION

In this paper, the problem of data detection and parameter estimation in low SNR and time-varying channel conditions has been addressed. PSP and conventional MLSD techniques have been thoroughly compared to extract performance/complexity tradeoffs as a function of the channel conditions.

To this aim, in the first part of the paper the detection capability of the NA-MLSD, CA-MLSD, and PSP approaches has been evaluated. Results, collected in Table I, show that there is a large range of channel parameter values in which PSP outperforms both NA-MLSD and CA-MLSD. This suggests that PSP can be considered as a valuable solution for the return link of multimedia satellite systems. At the fixed earth station, in fact, complexity is not at a prime, while phase noise is particularly relevant since the return link is generally characterized by low data rate due to the asymmetric nature of multimedia traffic. In addition, we have also addressed the problem of initial parameter acquisition showing how the reported results can be used as a good prediction tool for the performance of the CA-MLSD and PSP approaches when preamble-based acquisition systems are used.

In the last part of the paper, emphasis has been placed on the analysis of the A-MLSD estimation quality, one of the most interesting and yet unexplored research areas in the field of PSP-based systems. To this aim, we introduced the notions of decision-related tracker and virtual tracker. Numerical results have shown that, for all channel conditions, the PSP-based scheme performs significantly better than CA-MLSD.

REFERENCES


Andreas Polydoros (F’95) was born in Athens, Greece, in 1954. He received the Diploma in electrical engineering, in 1977, from the National Technical University of Athens, Greece, the MSEE degree, in 1979, from the State University of New York at Buffalo, and the Ph.D. degree in electrical engineering, in 1982, from the University of Southern California (USC).

He was a faculty member at USC in the Electrical Engineering Department/Systems and the Communication Sciences Institute (CSI) from 1982 to 1997 and a Professor since 1992. He co-directed CSI 1991–1993. Since 1997, he has been Professor and Director of the Electronics and Systems Laboratory, Division of Applied Physics, Department of Physics, University of Athens, Greece. His research interests include statistical communication theory with applications to wireless and wireline transmission (including spread–spectrum, cellular, satellite as well as high-throughput multi-carrier systems) signal detection and classification, data detection in uncertain environments, and multi-user radio networks. He has spent two decades in teaching, research and extensive consulting on these topics, both for the government and industry. His recent engagement in EU-funded research has produced extensive participation in various international research consortia via the IST Program. He is a co-inventor (with Prof. R. Raheli) of a U.S. patent on Per-Survivor Processing (PSP).

Dr. Polydoros is the recipient of a 1986 U.S. National Science Foundation Presidential Young Investigator Award. He has served as the Associate Editor for Communications of the IEEE TRANSACTIONS ON INFORMATION THEORY (1987–88), the Guest Editor of the July 1993 Special Issue on “Digital Signal Processing in Communications” for Digital Signal Processing: A Review Journal, a designated Area Editor for the international journal Wireless Personal Communications, and a co-Guest Editor of the March/April 1998 Special Issue on “Signal Processing in Telecommunications” for the European Transactions on Telecommunications.