Iterative Channel Estimation and Decoding for Convolutionally Coded Anti-Jam FH Signals

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***Abstract*—In this paper, an iterative algorithm for joint decoding and channel estimation in frequency-hopping (FH) networks is proposed. In the proposed algorithm, soft decoder outputs are used in the iterative estimation of the time-varying variance of the additive interference resulting from the sum of the thermal noise, partial-band noise jamming, and other-user interference. The soft outputs are also used in the estimation of the independent random carrier phases and multiplicative Rayleigh fading coefficients in different frequency dwells. The estimation process is further enhanced through the insertion of known symbols in the transmitted data stream. The proposed iterative symbol-aided demodulation scheme is compared with the coherent scenario, where the channel state information is assumed to be known *a priori* at the receiver, for both convolutionally coded and Turbo coded FH systems. The proposed iterative channel estimation approach is suited for slow FH systems where the channel dynamics are much slower than the hopping rate. This observation motivates the consideration of another robust approach for generating the log-likelihood ratios for fast hopping systems in additive white Gaussian noise channels. Simulation results that demonstrate the excellent performance of the proposed algorithms in various scenarios are also presented.**

***Index Terms*—Channel estimation, convolutional codes, frequency hopping, iterative decoding, partial band jamming, Turbo codes.**

I. Introduction

THE performance of frequency-hopping (FH) communication networks subject to partial band jamming and/or multiple access interference is generally unacceptable without the use of some form of forward error control (FEC) coding. Most of the work done on error control coding for FH networks was based on the use of RS codes with error-erasure decoding [1], [2].

Several erasure strategies have been proposed in the literature. Some of these strategies are based on the use of side information where some known symbols are inserted into each dwell and used at the receiver to identify which dwells were severely jammed and/or hit by other users' signals to erase them [2]. This approach suffers from two drawbacks. First, it may not be necessary to erase all the symbols in the jammed dwells since it is unlikely that all the received symbols in those dwells are corrupted. The erasure of all the symbols in the jammed dwells reduces the efficiency of information utilization at the receiver. Second, the transmission of known symbols in each dwell reduces the effective transmission rate especially when the hopping rate is fast. Other erasure strategies decide on a symbol-per-symbol basis using the soft outputs of the detector [1], [3]. The latter class of erasure strategies was shown to achieve better performance than the former one [1]. This can be attributed to the better utilization of the "soft" information contained in the received signal in the latter approach.

Recently, a new powerful class of concatenated convolutional codes was proposed by Berrou *et al.* [4], i.e., Turbo codes. These codes use parallel concatenation of two (or more) recursive systematic convolutional codes (constituent codes, CCs) fed by two information sequences of which the second is obtained from the first through the interposition of a long Interleaver. The fact that this coding structure was shown to yield a performance close to the Shannon capacity limit has stimulated a large amount of research from all around the world. This research has led to better understanding of their behavior, upper bounds to the maximum likelihood performance [5], and to the proposal of an alternative scheme based on the serial concatenation of interleaved codes which was shown to yield in some cases a superior performance [6].

One of the key factors contributing to the remarkable performance of Turbo codes is the elegant iterative soft-in/soft-out decoding structure whose performance was shown (via simulation) to approach that of maximum likelihood (ML) decoding, at signal-to-noise ratios (SNRs) very close to the Shannon limit, with much less complexity. This decoder is based on iteratively decoding the component codes and passing the so-called extrinsic information, which is a part of the component decoder soft output, to the next decoding stage. The soft-in/soft-out decoders, of the constituent codes, take as input the log-likelihood ratios of the received symbols plus the extrinsic information supplied by the other decoder. The impressive performance achieved by this iterative decoding architecture has encouraged several researchers to consider applying this iterative architecture in the other submodules of the receivers. In [7], Hagenauer coined the term "Turbo processing principle" for this architecture. He also pointed out that this receiver architecture can be used to improve the performance of other receiver submodules.

In this paper, we benefit from the Turbo processing principle to develop an iterative scheme for joint decoding and channel

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estimation in convolutionally coded and Turbo coded FH networks operated in the presence of additive thermal noise, additive partial band jamming, additive other user interference, and multiplicative flat Rayleigh fading. The proposed scheme utilizes the soft information, provided by the previous decoding step, to obtain better estimates of the "equivalent" channel parameters after each iteration. As such, the iterative scheme is applied to: 1) the estimation of the variance of the additive interference and 2) the estimation and subsequent mitigation of the multiplicative "interference" resulting from the random carrier phase introduced by the transmitter oscillator at the beginning of each frequency dwell and the complex Rayleigh fading coefficient.

To further enhance the estimation process, some known symbols are inserted by the transmitter at the beginning of each frequency dwell. In fact, at least one known symbol must be inserted into each frequency dwell to resolve the phase ambiguity at the receiver, as will be shown later. In this context, we compare the proposed iterative symbol-aided estimation algorithm with two other approaches. In the first one, which will be referred to as symbol-aided demodulation (SAD), only the known symbols are used in the estimation process. The second approach is the coherent demodulation scenario where knowledge of the multiplicative coefficients are assumed to be available *a priori* at the receiver. The bit error rate (BER) performance of this scheme serves as a lower bound on the performance of any practically realizable technique. In all cases, no prior knowledge about the additive interference variance is assumed at the receiver.

At the final stages in this paper preparation, we became aware of the work in [8]. This work discusses the application of Turbo codes to coherent FH systems with partial band jamming [8]. There are considerable differences between our approach and that presented in [8]. First, in [8] the FH channel with partial band jamming was modeled using a two-state model. The authors assumed *a priori* knowledge at the receiver of the noise variance in each state and the probability distribution of the two-state model. Therefore, the problem was formulated as a detection problem, i.e., detecting the channel state. By contrast, in our work we consider the case where the receiver does not have such *a priori* information about the channel. Therefore, we formulate the problem as an estimation problem, i.e., estimating the channel parameters. This formulation can handle the more general case of multiple jammers and/or other-user interference. Second, the authors in [8] only considered the case of coherent demodulation in additive white Gaussian noise (AWGN) channels. In this paper, however, we consider, in addition to the coherent case, more practical modulation/demodulation schemes, i.e., SAD and iterative SAD, both in AWGN and flat Rayleigh fading channels. Finally, the work in [8] was mainly proposed for the case of Turbo codes with maximum *a posteriori* probability (MAP) constituent decoders, whereas the proposed scheme in this paper is applicable to the more general case of convolutionally coded systems using any of the available soft-input/soft-output (SISO) decoders (MAP, Log-MAP, or SOVA) [4], [10].

The outline of the rest of this paper is as follows. The system model is presented in Section II. In Section III, we present the iterative approach for estimating the log-likelihood ratios. Numerical results that compare the performance of different schemes are presented in Section IV. Finally, Section V offers some concluding remarks.

II. System Model

In the system under consideration, the source generates K information bits which are encoded by an error control code C to produce code words of length N over the binary alphabet. The encoded symbols are mapped into binary phase shift keying (BPSK) constellation points using the modulation operator $f: 0 \rightarrow -1, 1 \rightarrow 1$ for transmission across the channel. Extension to QPSK modulation is straightforward. The encoded data stream is then interleaved using a block channel interleaver. This interleaving is necessary to avoid bursty error blocks at the input of the decoder. It is worth noting that this channel interleaving is different from any internal interleaving that may be used in the encoder as in the case of Turbo codes, for example. The interleaved data stream is grouped into blocks of N_b bits and each block is transmitted in a different frequency dwell. The choice of frequency dwells is done according to the hopping sequence assigned to the user. The hopping sequences assigned to different users are assumed to be independent random sequences that span the allowable frequency space. Also, all users and jammers are assumed to be synchronous on the frequency dwell level [11]. The received signal is thus the transmitted signal corrupted by additive noise and multiplicative interference. The base-band received signal r_k at time k is given by

$$r_k = \alpha_k d_k + I_k \tag{1}$$

where α_k is the multiplicative interference at time k resulting from the random carrier phase and Rayleigh fading; d_k is the base-band transmitted symbol i.e., $d_k \in \{-1, 1\}$; I_k is the additive noise sample at time k. For simplicity of notation, the signal power was normalized to one in (1) with the provision that the normalized variance of the additive noise will reflect the effective SNR. The additive noise is the sum of the thermal noise, partial band jamming [8], and other user interference. In this paper, we follow the model presented in [11] where both the partial band jamming and the multi-access interference were modeled as white Gaussian noise. The Gaussian modeling of the partial band jamming noise has been widely used in the literature (for example [1], [8]), and the Gaussian approximation for the other user interference was shown (in [11] and references therein) to give very accurate results for a wide range of SNRs. The importance of the the Gaussian approximation is that it allows for modeling the channel as a time-varying discrete channel where the additive noise is characterized as a zero mean white Gaussian process with normalized time-varying variance (σ_k^2). We also assume, without loss of generality, that there are m groups of jammers (users), where group i $(1 \leq i \leq m)$ has n_i jammers (users). Each jammer has a normalized jamming (interfering) single-sided power spectral density equal to N_i, and hitting probability[1] ρ_i, and the normalized thermal noise

[1]The hitting probability is the probability that this particular jammer (user) shares the same frequency dwell with the user of interest [11].

single-sided power spectral density is N_0. The random hopping sequence assumption ensures that each jammer (user) is independent from the others and that the noise variance is independent from one dwell to the next. Therefore, the total noise variance has the following conditional distribution:

$$\left(\sigma_k^2 = \frac{1}{2}\left(\sum_{i=1}^{m} k_i N_i + N_0\right) |(k_1, k_2, \ldots, k_m)\right) = \prod_{i=1}^{m} \binom{n_i}{k_i} \rho_i^{k_i}(1-\rho_i)^{(n_i-k_i)} \tag{2}$$

where k_i $(0 \leq k_i \leq n_i)$ is the number of jammers (users) of group i $(1 \leq i \leq m)$ sharing the same frequency dwell with the user of interest at time k.

We also assume perfect symbol synchronization and perfect power control, i.e., the receiver knows *a priori* the transmitted signal timing and power. The channel estimation problem is thus reduced to estimating the multiplicative interference term and the additive noise variance.

To further motivate the channel estimation problem in FH networks, consider the simple case of the additive white Gaussian noise (AWGN) channel and coherent demodulation, i.e., the receiver knows *a priori* the carrier phase. The AWGN channel assumption reduces the multiplicative interference term to

$$\alpha_k = e^{j\phi_k^{(o)}} \tag{3}$$

where $\phi_k^{(o)}$ is the uniformally distributed random phase introduced by the transmitter oscillator at the beginning of each frequency dwell. Since this phase is assumed to be known *a priori* at the receiver, r_k is multiplied by $e^{-j\phi_k}$ to obtain y_k and the log-likelihood ratio at time k is obtained as

$$L_k = \log \frac{p(y_k|d_k = 1)}{p(y_k|d_k = -1)} = \frac{2y_k}{\sigma_k^2}. \tag{4}$$

Now, even in this idealized example, the need for efficient channel estimation is clear. The importance of the accurate estimation of the additive noise variance is evident in (4). This can be attributed to two main reasons. First, in FH systems, the noise variance is changing with time due the time-varying nature of the jammers and other users sharing the same frequency spectrum, and hence, a different weighting term inversely proportional to the noise variance must be used in each log-likelihood ratio. Otherwise, the highly corrupted symbols will result in long bursty error blocks at the decoder output. Second, in the Turbo codes case, the input to each constituent decoder is updated by the extrinsic information supplied by the other constituent decoder. Hence, one needs to have an accurate estimate of the noise variance, even if it does not change with time, to calculate the log-likelihood ratios necessary for the iterative decoding algorithm. This comes in contrast to maximum likelihood decoding of convolutional codes where the knowledge of the noise variance is not required if it does not change with time.

In flat Rayleigh fading channels, the only difference in the model is related to the multiplicative interference term which is now given by

$$\alpha_k = a_k e^{j\left(\phi_k^{(f)} + \phi_k^{(o)}\right)} \tag{5}$$

where a_k is the fading amplitude characterized by a Rayleigh distribution with $E\left[a_k^2 = 1\right]$. $\phi_k^{(f)}$ is the uniformally distributed phase introduced by the channel. The complex Rayleigh fading coefficient is assumed to be constant across the whole frequency dwell and changes independently from one dwell to the next. Since both $\phi_k^{(f)}$ and $\phi_k^{(o)}$ have uniform distributions, then their sum is also characterized by a uniform distribution.

Several papers have studied the effect of errors in the SNR estimation on the performance of Turbo codes (e.g, [12]) in AWGN channels. These papers drew the conclusion that the performance of Turbo codes is generally robust to those errors. However, previous works have only considered the case of constant noise variance and coherent demodulation in AWGN channels. In this paper, we address the more general problem of convolutionally coded systems with time-varying noise variance in AWGN and flat Rayleigh fading channels.

III. Iterative Decoding and Channel Estimation

In the proposed algorithm, the channel estimator uses the soft information after each decoding iteration to update the channel parameters' estimates. This approach can be used with any demodulation scheme and is also independent of the decoding algorithm used by the constituent decoder(s). However, unlike the traditional Turbo decoder, the decoders now need to update the reliabilities of both the information and parity bits (similar to serially concatenated codes [10]). Throughout this paper, we have assumed that the receiver does not have prior knowledge of the channel parameters' statistics.

A. AWGN Channels

In this scenario, the receiver is assumed to have prior knowledge of the carrier phase, and hence, the only unknown parameter that needs to be estimated is the effective noise variance. The estimation, and subsequent mitigation, of the multiplicative interference is considered in Section III-B. We also assume that the channel variations are much slower than the hopping rate such that the additive noise power remains the same across the whole frequency dwell.

First, the carrier phase shift is compensated by multiplying r_k with $e^{-j\phi_k^{(o)}}$ to obtain y_k. Assuming, without loss of generality, that the vector $\underline{d} = [d_k, d_{k+1}, \ldots, d_{k+N_b-1}]$ is transmitted in the same frequency dwell, the log-likelihood ratio at time $k \leq t \leq k + N_b - 1$ is given by

$$L_t = \log \frac{P\left(\underline{y}|d_t = 1\right)}{P\left(\underline{y}|d_t = -1\right)} \tag{6}$$

where $\underline{y} = [y_k, \ldots, y_{k+N_b-1}]$. Denote

$$\mathcal{D}^+ = [d_k, \ldots, d_{t-1}, +1, d_{t+1}, \ldots, d_{k+N_b-1} : d_k \in \{1, -1\}, \ldots, d_{k+N_b-1} \in \{-1, 1\}]. \tag{7}$$

The set $\mathcal{D}^-$ can be similarly defined. The log-likelihood ratio can now be written as (8), shown at the bottom of the page.

After each decoding iteration, $P(d_k, \ldots, d_{t-1}, d_{t+1}, \ldots, d_{N_b+k-1} | y_k, \ldots, y_{N_b+k-1})$ must be *estimated* from the soft decoder outputs in order to update the log-likelihood ratio as in (8). Unfortunately, this computation is generally intractable without further assumptions. Hence, we introduce the following independence assumption:

$$P(d_k, \ldots, d_{t-1}, d_{t+1}, \ldots, d_{N_b+k-1} | y_k, \ldots, y_{N_b+k-1}) = \prod_{k \le j \le k+N_b-1;\, j \ne t} P(d_j | y_k, \ldots, y_{N_b+k-1}). \quad (9)$$

This assumption is justified by the channel interleaving used to distribute the encoded data stream across the different frequency dwells. For simplicity of notation, $P(d_j | y_k, \ldots, y_{N_b+k-1})$ will be referred to as $P(d_j)$ in the following. The MAP detector is then given by

$$L_t = \log \frac{\sum_{\underline{d} \in \mathcal{D}^+} P(y_t | \underline{d}) \prod_{k \le j \le k+N_b-1,\, j \ne t} P(d_j)}{\sum_{\underline{d} \in \mathcal{D}^-} P(y_t | \underline{d}) \prod_{\le j \le k+N_b-1,\, j \ne t} P(d_j)} \quad (10)$$

where $P(d_j)$ is obtained from the soft output of the previous decoding iteration as

$$P(d_j = 1) = \frac{e^{\lambda_j}}{1 + e^{\lambda_j}} \quad (11)$$

$$P(d_j = -1) = \frac{1}{1 + e^{\lambda_j}} \quad (12)$$

where λ_j is the output log-likelihood ratio of the previous iteration. In the first iteration, it is assumed that $P(d_j = 1) = P(d_j = -1) = 0.5$.

Let s_t be the additive noise variance at time t, then we have

$$\begin{aligned} P(y_t | \underline{d}, y_k, \ldots, y_{N_b+k-1}) &= \int P(y_t, s_t | \underline{d}, y_k, \ldots, y_{N_b+k-1})\, ds_t \\ &= \int P(y_t | d_t, s_t)\, P(s_t | d_k, y_k, \ldots, y_{t-1}, d_{t-1}, \\ &\qquad y_{t+1}, d_{t+1}, \ldots, y_{N_b+k-1}, d_{k+N_b-1})\, ds_t \\ &= \int \frac{1}{\sqrt{2\pi s_t}} e^{-(y_t - d_t)^2 / 2s_t} \\ &\qquad \times P(s_t | d_k, y_k, \ldots, y_{N_b+k-1}, d_{N_b+k-1})\, ds_t. \quad (13) \end{aligned}$$

From (13), it is clear that in order to compute the MAP estimate of the log-likelihood ratio, the conditional distribution of the noise variance must be known *a priori* at the receiver. Even if this information is available at the receiver, the integration with respect to "s_t" does not seem to have a closed-form solution for most practical distributions. Thus, instead of the integration with respect to "s_t," we use the ML estimate of the noise variance obtained from the received symbols $(y_k, \ldots, y_{t-1}, y_{t+1}, \ldots, y_{t+N_b-1})$ to compute $P(y_t | \underline{d}, y_k, \ldots, y_{N_b+k-1})$. This results in (14), shown at the bottom of the page, where

$$\sigma_{t,\mathrm{ML}}^2 = \sum_{k \le j \le k+N_b-1,\, j \ne t} \frac{(y_j - d_j)^2}{N_b - 1}. \quad (15)$$

The main drawback of this approach is the exponential computational complexity involved in the summations (i.e., proportional to 2^{N_b}). This complexity may be prohibitive in many applications which motivates the investigation of alternative suboptimum approaches with reasonable complexity.

To this end, let's assume for now that only a single observation y_j is used to estimate $\sigma_k^2 = \sigma_t^2 = \sigma_{k+N_b-1}^2 = \sigma^2$. Let $p_{1j} = P(d_j = 1)$ as obtained in (11) and $p_{0j} = P(d_j = -1)$ as in (12). If d_j is known *a priori* at the receiver $p_{0j} \in \{0, 1\}$ the ML estimator is

$$\sigma_{\mathrm{ML}}^2 = (y_j - d_j)^2 \quad (16)$$

where $d_j = -1$ for $p_{0j} = 1$ and $d_j = 1$ for $p_{0j} = 0$.

This observation suggests the following suboptimum variance estimator

$$\begin{aligned} \hat{\sigma}^2 &= E_{d_j}\left[(y_j - d_j)^2\right] + c, \\ &= p_{0j}(y_j + 1)^2 + (1 - p_{0j})(y_j - 1)^2 + c \end{aligned} \quad (17)$$

where $c = 2(1 - 2p_{0j})^2 - 2$ is a constant added to unbias the estimator. Now, going back to the original problem, the estimate

$$\begin{aligned} L_t &= \frac{\sum_{\underline{d} \in \mathcal{D}^+} P(\underline{y}, d_k, \ldots, d_{t-1}, d_{t+1}, \ldots, d_{N_b+k-1} | d_t = 1)}{\sum_{\underline{d} \in \mathcal{D}^-} P(\underline{y}, d_k, \ldots, d_{t-1}, d_{t+1}, \ldots, d_{N_b+k-1} | d_t = -1)} \\ &= \frac{\sum_{\underline{d} \in \mathcal{D}^+} P(y_t | \underline{d}, y_k, \ldots, y_{N_b+k-1}) P(y_k, d_k, \ldots, y_{t-1}, d_{t-1}, y_{t+1}, d_{t+1}, \ldots, y_{N_b+k-1}, d_{N_b+k-1})}{\sum_{\underline{d} \in \mathcal{D}^-} P(y_t | \underline{d}, y_k, \ldots, y_{N_b+k-1}) P(y_k, d_k, \ldots, y_{t-1}, d_{t-1}, y_{t+1}, d_{t+1}, \ldots, y_{N_b+k-1}, d_{N_b+k-1})} \\ &= \frac{\sum_{\underline{d} \in \mathcal{D}^+} P(y_t | \underline{d}, y_k, \ldots, y_{N_b+k-1}) P(d_k, \ldots, d_{t-1}, d_{t+1}, \ldots, d_{N_b+k-1} | y_k, \ldots, y_{N_b+k-1})}{\sum_{\underline{d} \in \mathcal{D}^-} P(y_t | \underline{d}, y_k, \ldots, y_{N_b+k-1}) P(d_k, \ldots, d_{t-1}, d_{t+1}, \ldots, d_{N_b+k-1} | y_k, \ldots, y_{N_b+k-1})} \end{aligned} \quad (8)$$

$$L_t = \log \left\{ \frac{\sum_{\underline{d} \in \mathcal{D}^+} \left[\frac{1}{\sqrt{\sigma_{t,\mathrm{ML}}^2}} e^{\left(-(y_t - 1)^2 / 2\sigma_{t,\mathrm{ML}}^2\right)} \prod_{k \le j \le k+N_b-1,\, j \ne t} P(d_j) \right]}{\sum_{\underline{d} \in \mathcal{D}^-} \left[\frac{1}{\sqrt{\sigma_{t,\mathrm{ML}}^2}} e^{\left(-(y_t + 1)^2 / 2\sigma_{t,\mathrm{ML}}^2\right)} \prod_{k \le j \le k+N_b-1,\, j \ne t} P(d_j) \right]} \right\} \quad (14)$$

of the noise variance at time t based on the other $N_b - 1$ samples can be obtained as

$$\hat{\sigma}_t^2 = \frac{1}{N_b - 1} \sum_{k \le j \le k+N_b-1,\ j \ne t} \left[p_{0j}(y_j + 1)^2 + (1 - p_{0j})(y_j - 1)^2 \right] + c. \quad (18)$$

The log-likelihood ratio at time t is then obtained from the estimated noise variance as

$$L_t = \frac{2y_t}{\hat{\sigma}_t^2}. \quad (19)$$

This algorithm offers two immediate advantages. First, it is naturally adapted to the iterative decoding structure used for decoding Turbo codes and is independent of the algorithm used in each decoding step. Second, the complexity of the algorithm only grows linearly with the number of symbols sharing the same noise variance (i.e., transmitted in the same frequency dwell).

It is easy to see that the proposed iterative scheme can only be used for slow FH networks where the channel dynamics are much slower than the hopping rate. This limitation results from the assumption that all the symbols in the same dwell are corrupted by white noise samples with the same variance. This assumption is not necessarily valid in all cases. For example, in the case of fast hopping networks, networks operated asynchronously, and networks subject to rapidly varying jamming, this assumption does not hold. In these situations, the need arises for a robust estimator that does not depend on this assumption.

The generalized ML ratio test is used to derive a robust estimate for the log-likelihood ratio in these cases

$$L_t = \log \frac{\frac{1}{\sigma_1} e^{\left(-(y_t-1)^2/2\sigma_1^2\right)}}{\frac{1}{\sigma_0} e^{\left(-(y_t+1)^2/2\sigma_0^2\right)}} \quad (20)$$

where σ_1 and σ_0 are the variance values which maximize $P(y_t|d_t = 1)$ and $P(y_t|d_t = -1)$, respectively. These values are given by

$$\sigma_1 = |y_t - 1| \quad (21)$$

$$\sigma_0 = |y_t + 1| \quad (22)$$

and, substituting these values back into (20), we obtain

$$L_t = \log \frac{|y_t + 1|}{|y_t - 1|}. \quad (23)$$

As expected in this estimator, $L_t \to 0$ as $y_t \to \infty$ or $-\infty$ which gives an indication that the estimate will be more robust to the effect of high jamming powers. This will be validated by simulation results in Section IV.

Finally, for comparison purposes, we consider the simplest scheme where the log-likelihood ratio is simply given by

$$L_t = y_t. \quad (24)$$

This scheme will be referred to as the No Side Information (NSI) in the numerical results section. It is worth noting that the NSI log-likelihood ratios are optimal for maximum likelihood decoding of convolutional codes in systems characterized by a constant noise variance.

B. Flat Rayleigh Fading Channels

In this section, we consider the estimation of the multiplicative interference term in flat Rayleigh fading channels. Also, it will be shown that, with only a minor modification, the same algorithm can used to estimate the random carrier phase in AWGN channels. Based on the slow hopping assumption, the complex fading gain is constant across the whole dwell.

In the new scenario, the receiver needs to estimate the complex fading gain as well as the effective noise variance in each dwell. At least one known symbol must be transmitted at the beginning of each dwell to resolve the phase ambiguity. The number of known symbols in a single dwell is referred to as n and, hence, the total number of transmitted symbols in the dwell is $N_b + n$.

Similar to (14), the ML estimates of the complex fading gain and noise variance are used to obtain the log-likelihood ratio as shown in (25), at the bottom of the page, where

$$\hat{a}_t e^{j\hat{\phi}_t} = \frac{1}{n + N + b} \sum_{k \le j \le k+n+N_b-1,\ j \ne t} d_j r_j \quad (26)$$

$$\sigma_{t,\mathrm{ML}}^2 = \frac{1}{2(N_b + n - 1)} \times \sum_{k \le j \le k+n+N_b-1,\ j \ne t} \left| r_j - d_j \hat{a}_j e^{j\hat{\phi}_j} \right|^2. \quad (27)$$

It is easy to see that this scheme also suffers from the high computational complexity that grows exponentially with the number of symbols in the same dwell. This motivates the following suboptimal scheme whose complexity only grows linearly with the number of symbols $n + N_b$. To estimate the complex fading gain, we follow the same suboptimal strategy used for estimating the noise variance in Section III-A:

$$\hat{a}_t e^{j\hat{\phi}_t} = \frac{1}{b} \sum_{k \le j \le k+n+N_b,\ j \ne t} \left[(1 - 2p_{0j}) r_j \right] \quad (28)$$

$$L_t = \log \left\{ \frac{\sum_{\underline{d} \in \mathcal{D}^+} \left[\frac{1}{\sigma_{t,\mathrm{ML}}^2} e^{\left(\left| r_t - \hat{a}_t e^{j\hat{\phi}_t} \right|^2 / 2\sigma_{t,\mathrm{ML}}^2 \right)} \prod_{k \le j \le k+N_b+n-1,\ j \ne t} P(d_j) \right]}{\sum_{\underline{d} \in \mathcal{D}^-} \left[\frac{1}{\sigma_{t,\mathrm{ML}}^2} e^{\left(\left| r_t + \hat{a}_t e^{j\hat{\phi}_t} \right|^2 / 2\sigma_{t,\mathrm{ML}}^2 \right)} \prod_{k \le j \le k+N_b+n-1,\ j \ne t} P(d_j) \right]} \right\} \quad (25)$$

where $b = \sum_{k \le j \le k+N_b-1,\, j \ne t} (1-2p_{0j})^2$ is used to unbias the estimator. Assuming, without loss of generality, that the known symbols are ones implies that $p_{0j} = 0$ for these symbols. For the data symbols, p_{0k} is obtained from the previous decoding iteration as given by (12). Using the estimates of the complex fading gain, the suboptimal estimate for the noise variance can now be obtained as

$$\hat{\sigma}_t^2 = \frac{1}{\alpha} \sum_{k \le j \le k+N_b+n-1,\, j \ne t} \left[p_{0j} \left| r_j + \hat{a}_j e^{j\hat{\phi}_j} \right|^2 + (1-p_{0j}) \left| r_j - \hat{a}_j e^{j\hat{\phi}_j} \right|^2 \right] + \beta \quad (29)$$

where α and β are constants adjusted to unbias the estimator. The log-likelihood ratio is now given by

$$L_t = \frac{2\mathrm{Re}\left(r_t \hat{a}_t e^{-j\hat{\phi}_t} \right)}{\hat{\sigma}_t^2}. \quad (30)$$

For the sake of comparison, we considered also the SAD approach where $\hat{a}_t e^{-j\hat{\phi}_t}$ is estimated as in (28), however, using the known symbols only.

In AWGN channels, the only difference is that the fading amplitude is known to be equal to one. The receiver still needs to estimate the carrier phase in each dwell. Hence, the only modification to the algorithm is to set $\hat{a}_t = 1$, and the estimate of the carrier phase at time t is obtained from

$$e^{j\hat{\phi}_t} = \frac{1}{b_1} \sum_{k \le j \le k+n+N_b-1,\, j \ne t} [(1-2p_{0j}) r_j] \quad (31)$$

where b_1 is now adjusted to keep the modulus equal to one.

IV. Performance Results

A. Coded FH System Parameters

In all the simulations pertaining to Turbo codes, we used rate $r = 1/3$ code using four-state recursive systematic constituent encoders with octal generators $(1/5_8, 1/7_8)$. The interleaver length is 200 bits. In addition to the internal random Turbo interleaver [4], an outer block interleaver of the same block length is used to distribute the encoded symbols among the different dwells. The number of decoding iterations is 5 and the decoding algorithm used by the constituent decoders is the SOVA. The log-likelihood ratios computed throughout the paper correspond to the channel intrinsic information used by the Turbo decoder [6]. After each half iteration by one constituent decoder, the log-likelihood ratios are updated and passed, along with the soft extrinsic information [6], to the other constituent decoder.

In the convolutional codes case, a rate $r = 1/2$ nonsystematic code with generator polynomials $(5_8, 7_8)$ is used. The depth of the channel interleaver used is 400 symbols which is equivalent to 200 bits. For the iterative approach, the number of decoding iterations is 3.

Unless otherwise stated, we assumed that the number of transmitted information symbols per frequency dwell is $N_b = 10$. The simulations were terminated after 15 frame errors.

B. Iterative Estimation of the Additive Noise Variance

Figs. 1 and 2 report the performance of the different decoding strategies for Turbo coded FH networks operated in the presence of partial band jamming in AWGN channels. The energy per bit to thermal noise ratio E_b/N_0 is set to 20 dB and assumed to be known *a priori* at the receiver. The receiver is also assumed to know *a priori* the carrier phase. We assumed the existence of one jammer that distributes its power equally over a fraction ρ of the frequency range. The single-sided power spectral density of the jammer in the frequency range where it exists is N_j. In Fig. 1 $\rho = 0.6$, whereas in Fig. 2 $\rho = 0.4, 0.6$, respectively. Also, in Fig. 1, we included the performance with perfect channel state information (CSI) at the receiver which serves as a lower bound on the BER achieved by any channel estimation scheme.

Fig. 1 compares the performance of the proposed iterative scheme for estimating the jamming power and the NSI case. In the range between 10^{-2} and 10^{-3} BERs, the iterative scheme provides a gain of more than 3 dB compared to the NSI case. Fig. 2 compares the performance of the robust scheme described by (23) and the NSI case. It is clear that the performance of the robust scheme is less sensitive to variations in E_b/N_j especially for low ρ and low E_b/N_j which was expected. Also, it is shown that the gain provided by the robust scheme compared to the NSI case increases as ρ decreases.

The multiple access capability of FH networks employing the iterative decoding and channel estimation approach is investigated in Figs. 3 and 4 for both convolutionally coded and Turbo coded FH systems, respectively. We considered the case of a single cell and the frequency utilization is defined as

$$\eta = \frac{K_u \cdot r}{q}$$

where K_u is the total number of users which is to set to 50 in our simulations, r is the code rate, and q is the number of frequency slots. The other user interference is modeled as a Gaussian process with zero mean and variance

$$\sigma^2 = (1+\epsilon) \cdot E_s \quad (32)$$

where $E_s = E_b \cdot r$ and ϵ is the power control error which is set to −3 dB.[2] We also assumed $E_b/N_0 = 6$ dB. From the figures, it is observed that the performance gain of the proposed scheme is more significant in convolutionally coded systems compared to systems employing Turbo codes. One possible reason for this trend is the steep performance characteristics of Turbo codes [4].

C. Iterative Symbol-Aided Demodulation

In Figs. 5 and 6, we study the performance of different multiplicative interference estimation schemes in convolutionally coded FH networks operated in AWGN and Rayleigh fading channels. In these figures, the number of known symbols inserted in the beginning of each dwell (n) is varied. It is worth noting that increasing the number of known symbols, per dwell,

[2]The value of the power control error was chosen somewhat arbitrarily, however, we believe that it does not change the conclusion that the proposed scheme outperforms the NSI case significantly.

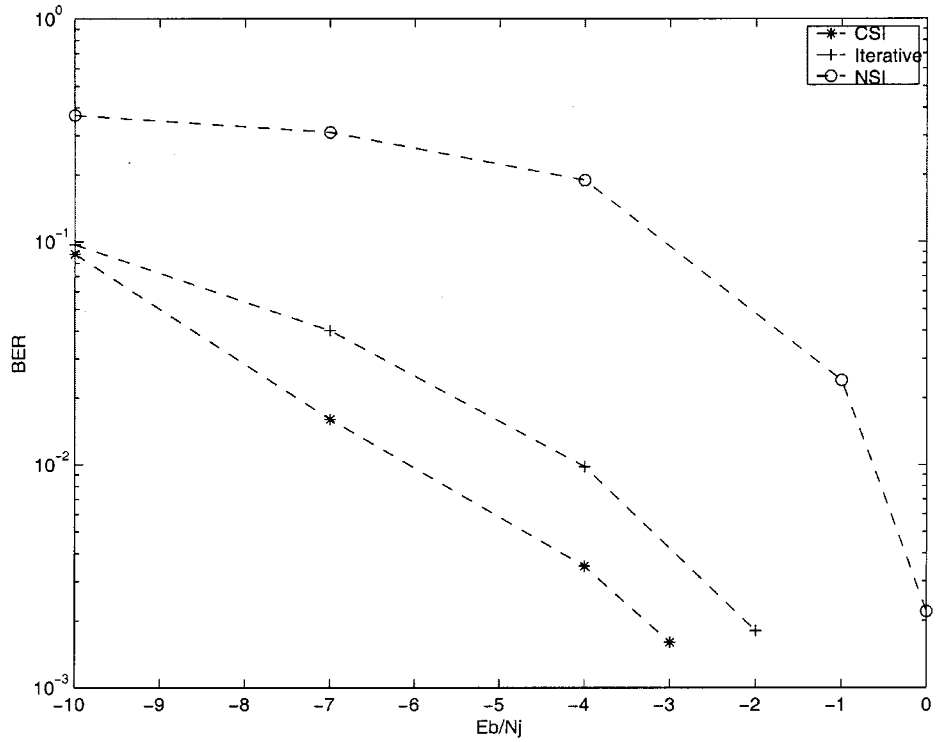

Fig. 1. BER performance for Turbo coded FH/SSMA networks subject to partial band jamming.

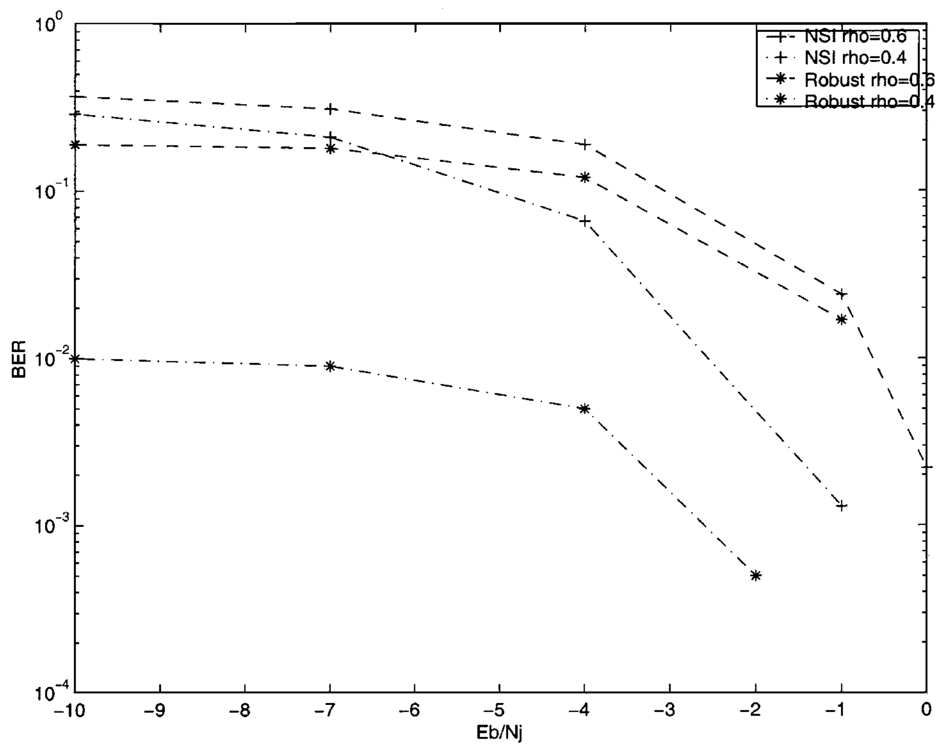

Fig. 2. BER performance for Turbo coded FH networks subject to partial band jamming.

decreases the achievable throughput. The symbol energy is now given by

$$E_s = \frac{E_b \cdot r \cdot N_b}{N_b + n}$$

and the throughput loss is

$$\frac{n \cdot r}{N_b + n}$$

which amounts to the effective reduction in the *uncoded* infor-

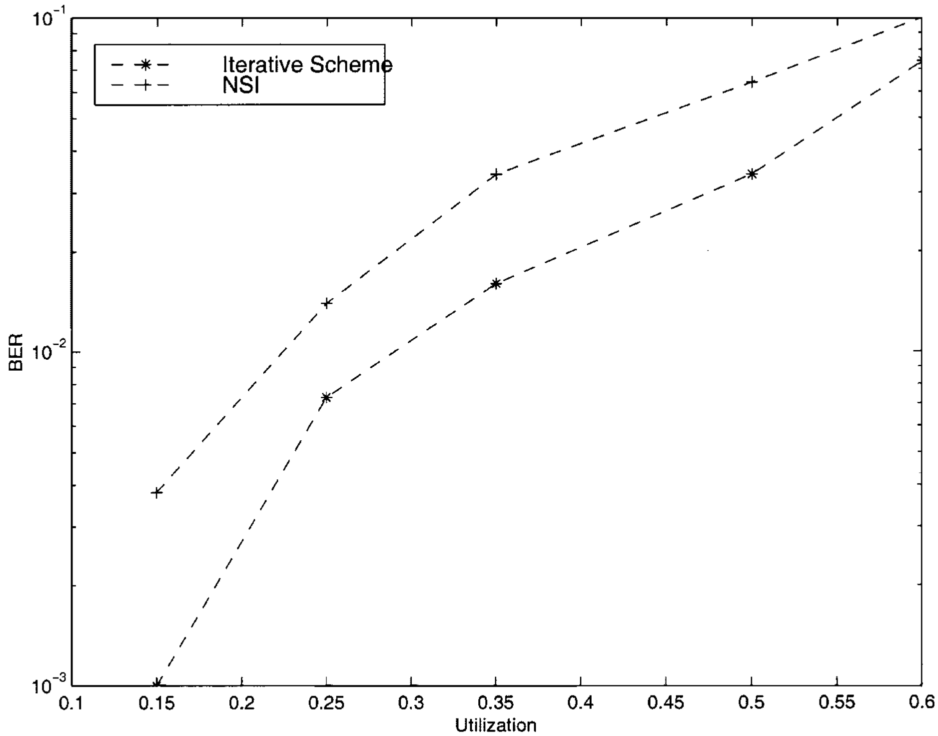

Fig. 3. BER versus frequency utilization for convolutionally coded FH networks.

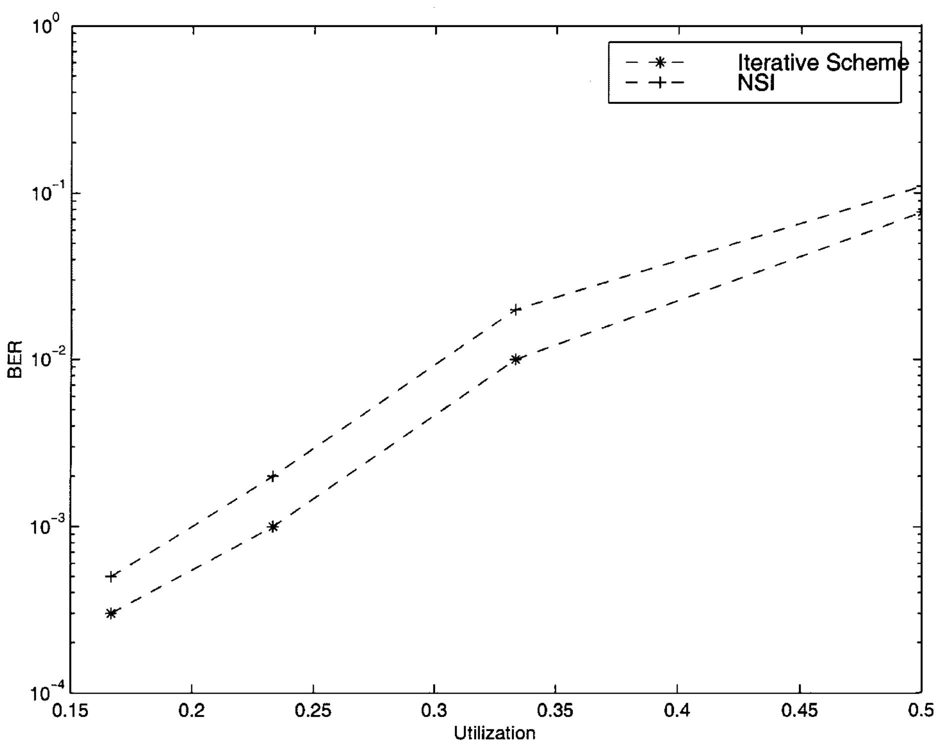

Fig. 4. BER versus frequency utilization for Turbo coded FH networks.

mation throughput due to the insertion of known symbols. In the differential binary phase shift keying (DPSK) case, only one known symbol is transmitted at the beginning of each dwell. This is necessary to resolve the phase ambiguity. The conventional symbol-aided demodulation where only the known symbols are used in the estimation is referred to as (SAD) in the figures. The proposed iterative SAD algorithm is referred to as (iterative). It is clear that both the SAD and iterative SAD schemes do not suffer from the error floor experienced in the DPSK case. The performance of the iterative scheme is shown to be uniformly better than the SAD, with the same n, and DPSK schemes. For the SAD technique, increasing n from 2 to 3 im-

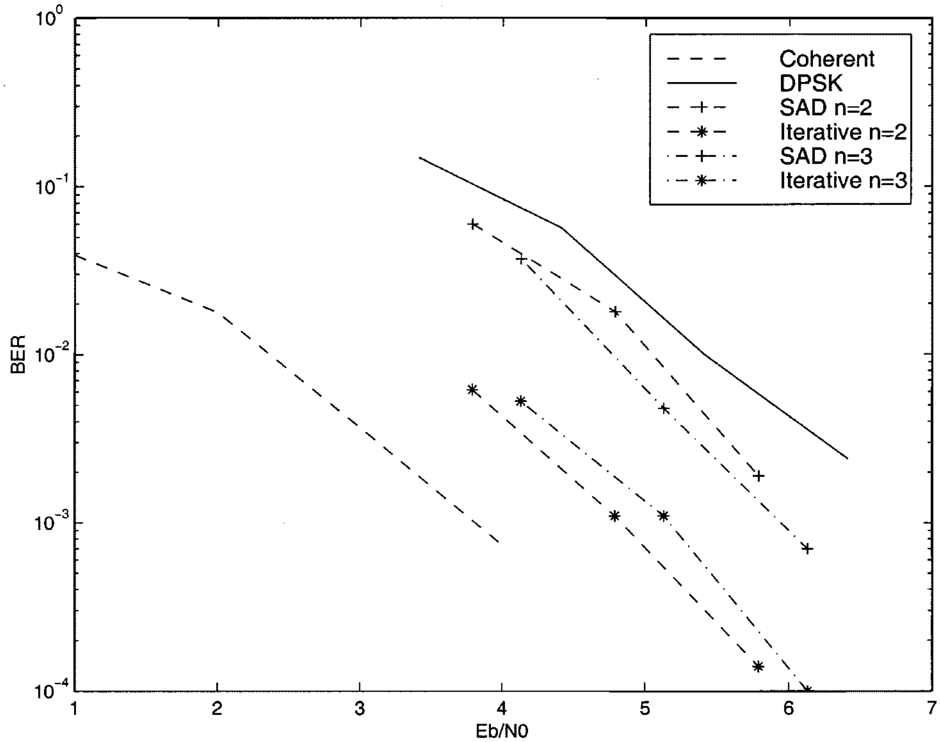

Fig. 5. BER performance for convolutionally coded FH networks in AWGN channels.

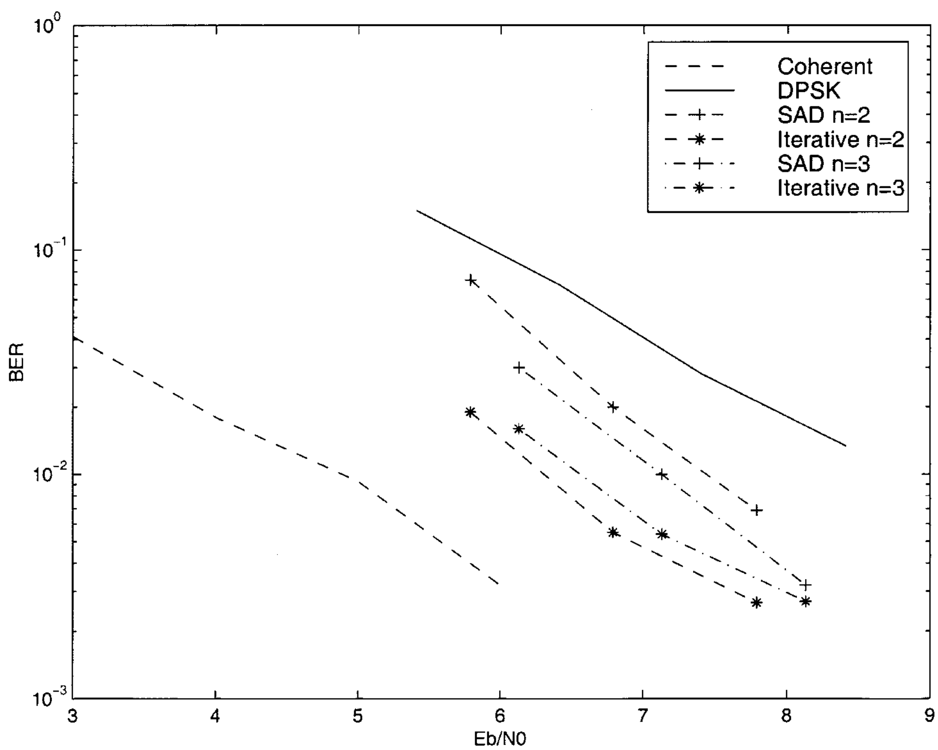

Fig. 6. BER performance for convolutionally coded FH networks in Rayleigh fading channels.

proves the performance slightly. Quite interestingly, the same change in the number of known symbols degraded the performance of the iterative SAD scheme. This can be explained when we consider the reduction in the symbol energy, for a fixed energy per bit, resulting from the addition of more known symbols. In this particular case, the benefit of adding more known symbols was overweighted by the negative impact resulting from the reduction in the symbol energy. In fact, for both the iterative SAD and SAD schemes, there exists an optimum number of known symbols. This optimum number will, in general, de-

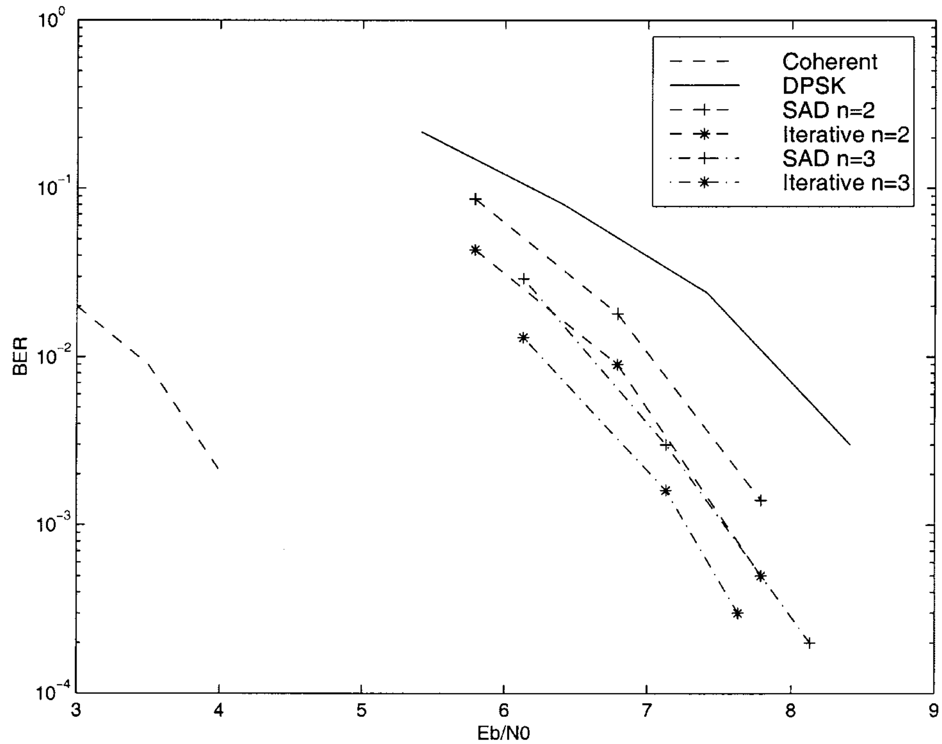

Fig. 7. BER performance for Turbo coded FH networks in Rayleigh fading channels.

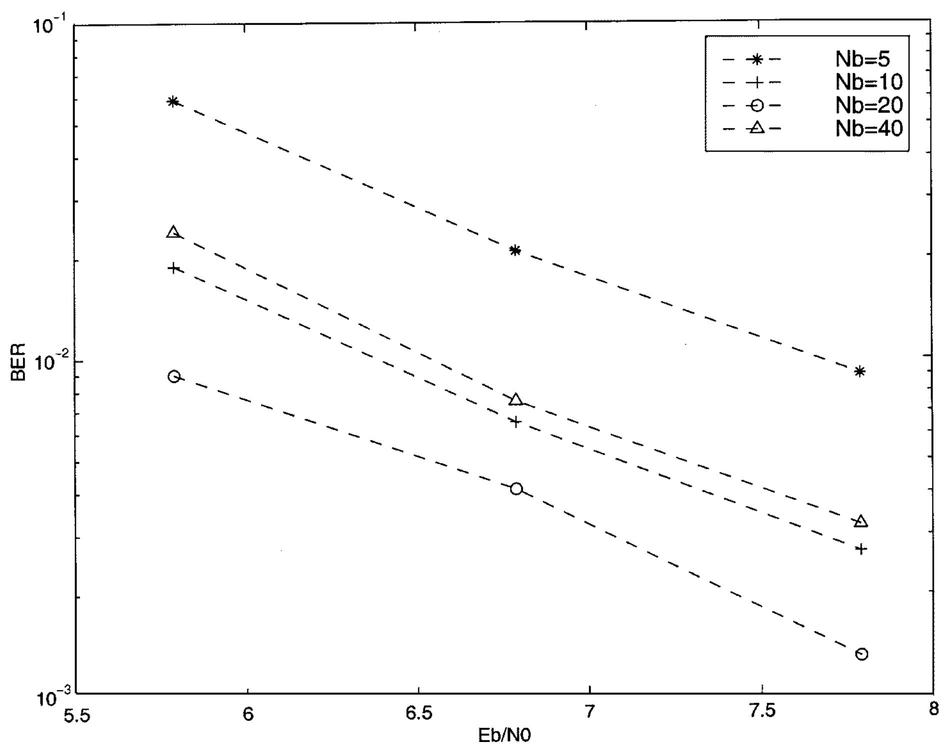

Fig. 8. BER performance for convolutionally coded FH networks in Rayleigh fading with different dwell sizes.

pend on the network configuration (i.e., hopping rate, channel dynamics, code rate, and the power of the used code). It is clear that the iterative scheme with $n = 2$ is the best solution for this network configuration.

A similar performance comparison is repeated in Fig. 7 for Turbo coded FH systems in Raleigh fading channels. In general, trends similar to the convolutional code case are observed. However, in this case, $n = 3$ is better than $n = 2$ for the iterative SAD scheme. This can be attributed to the lower coding rate used, and hence, lower symbol energy for the known symbols. One also observes that the advantage of the iterative SAD scheme is less than the convolutional code case.

In Fig. 8, we investigate the effect of dwell size (i.e., N_b) on the performance of convolutionally coded systems in flat Rayleigh fading channels. The number of known symbols n was varied in proportion to N_b to keep the throughput loss fixed at 1/12. The iterative SAD scheme was used for channel estimation. It is clear that, for the same throughput loss and delay, there exists an optimum value for N_b. This optimum value depends on the different system parameters. This can be explained as follows. Increasing N_b allows for the insertion of more known symbols to enhance the channel estimation process. However, increasing N_b will also result in more correlation in the same decoding frame, and consequently, increasing the probability of error propagations. The optimum N_b achieves the best trade-off between these two contending effects.

V. Conclusion

In this paper, we have proposed an iterative scheme for joint decoding and channel estimation in frequency hopping multiple access networks. First, in AWGN channels, we showed that the proposed iterative algorithm provides superior performance to the NSI case in the presence of partial band jamming or other-user interference. We have also proposed a robust estimation scheme based on the generalized ML ratio test for estimating the log-likelihood ratios in fast hopping networks. The performance of this robust algorithm was also shown to be significantly better than that of the NSI case. Second, for both AWGN and flat Rayleigh fading channels, we developed an iterative SAD approach for estimating the multiplicative interference term and the additive noise variance. This approach was shown to outperform both the DPSK and traditional SAD approaches in various scenarios.

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