Joint Demodulation of Cochannel Signals Using MLSE and MAPSD Algorithms

K. Giridhar† Sujai Chari‡ John J. Shynk† Richard P. Gooch‡

† Center for Information Processing Research
Dept. of Elec. and Comp. Engineering
University of California
Santa Barbara, CA 93106

‡ Applied Signal Technology, Inc.
160 Sobrante Way
Sunnyvale, CA 94086

Abstract

Sequence estimation and symbol detection algorithms for the demodulation of cochannel narrowband signals in additive noise are proposed. These algorithms are based on the maximum likelihood (ML) and maximum a posteriori (MAP) criteria for the joint recovery of both cochannel signals. The error rate performance characteristics of these nonlinear algorithms are investigated through computer simulations.

1 Introduction

Frequency-reuse systems such as digital cellular radio often encounter cochannel interference, whereby one or more (interfering) secondary signals are present at the receiver along with the (desired) primary signal. In addition, the primary and secondary signals encounter noisy, narrowband channel characteristics, leading to intersymbol interference (ISI). The degradation in quality due to cochannel interference is often more severe than that caused by additive noise or ISI.

Usually, we would like to recover only the primary signal using interference suppression techniques. However, in certain applications we are interested in the *joint recovery* of all data streams. In this paper, we consider a communication model with one secondary cochannel signal to be jointly recovered along with the primary data stream. Since the signal spectra overlap, a linear filter alone cannot be used to accurately demodulate the two signals. Instead, *nonlinear* techniques are needed to achieve an acceptable error-rate performance.

It should be mentioned that although this joint recovery problem has been considered in broadband systems (e.g., see [1] for a survey of multiuser detection techniques in CDMA systems), it has rarely been addressed for uncoded narrowband signal reception. Recently, Gooch and Sublett [2] described a narrowband cochannel recovery technique using a quasi-linear "demod-remod" approach.

In this paper we present nonlinear cochannel demodulation techniques based on ML sequence estimation (MLSE) and MAP symbol detection (MAPSD). Since both the primary and secondary symbols are jointly recovered, we refer to the corresponding algorithms as joint MLSE (JMLSE) and joint MAPSD (JMAPSD). These optimal estimation techniques have a superior bit error rate (BER) performance compared to the ideal decision-feedback equalizer (DFE), but are computationally more expensive. However, it is possible to implement the JMAPSD algorithm using a suboptimal two-stage configuration, thereby reducing its computational complexity.

2 Cochannel Measurement Model

The cochannel system model is shown in Figure 1. The transmitted low-pass equivalent waveforms can be represented by

$$s_m(t) = \sum_{k=-\infty}^{\infty} d_m(k)g(t-kT),\ m = 1,2 \qquad (1)$$

where T is the symbol duration, and $\{d_1(k)\}$ and $\{d_2(k)\}$ are the primary and secondary source symbols, respectively. The pulse function $g(t)$ has a raised-cosine response with a finite duration of $2T$ seconds. We propose a $T/2$-spaced equalizer implementation to eliminate the need for a whitening matched filter (which cannot be ideally defined for this cochannel

*This work was sponsored in part by the University of California MICRO Program and Applied Signal Technology, Inc.

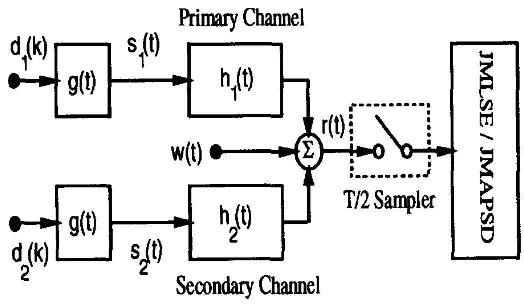

Figure 1: Cochannel system model.

problem), and to take advantage of the excess bandwidth in $g(t)$. Hence, the discrete measurement samples of the received signal $r(t)$ at the output of the $T/2$ sampler in Figure 1 are given by

$$r_j(k) = \sum_{m=1}^{2} \sum_{n=0}^{L_m} f_{m,n}(k) d_m(k-n) + w_j(k), \;\; j = 1, 2 \tag{2}$$

where $r_1(k) = r(kT)$ and $r_2(k) = r(kT + T/2)$. The sequences $\{w_j(k)\}$ are assumed to be mutually uncorrelated, white, and Gaussian with zero mean and variance σ_w^2. The lengths of the primary and secondary channels are $L_1 + 1$ and $L_2 + 1$, respectively. The channel coefficients $\{f_{m,n}(k)\}$ represent the convolution of the ISI channels $\{h_m(t)\}$ with the transmit filter $g(t)$, sampled at $T/2$ seconds. Note that perfect timing synchronization is implicitly assumed in the above model (although the $T/2$-spaced equalizer is nearly insensitive to symbol timing offset). The goal of the receiver is to accurately recover the primary and secondary sequences, $\{d_1(k)\}$ and $\{d_2(k)\}$, given accurate estimates of the channel coefficients, $\{f_{1,n}(k)\}$ and $\{f_{2,n}(k)\}$.

3 Joint ML Sequence Estimation (JMLSE)

The objective of MLSE is to determine the one sequence $d_i^k = \{d_i(k), \ldots, d_i(0)\}$ out of all possible transmitted symbol sequences that is closest (according to a specific probability measure) to the actual received sequence $r^k = \{r(k), \ldots, r(0)\}$. The Viterbi algorithm (VA) is a practical way of implementing optimal MLSE [3]. It utilizes a finite-state machine description of the FIR channel, such that the received symbol at time k is a function of only the present symbol $d(k)$ and L previously transmitted symbols $\{d(k-1), \ldots, d(k-L)\}$. These previous symbols are defined as a state; for example, the i^{th} state (of the M^L possible states where M is the number of source symbols) is defined by $s_i^{k-1,L} = \{d_i(k-1), \ldots, d_i(k-L)\}$. It is evident that $s_i^{k-1,L}$ can transition to M possible states at time k, and that it could have been reached from M different states at time $k-2$. The algorithm maintains a decoding trellis with M^L nodes and an equal number of survivor sequences (one of which is the ML sequence). The VA decisions are computed by truncating the survivors after about $4L$ symbols [3].

For the cochannel interference scenario, we are interested in computing ML estimates of both the primary and secondary signals. The JMLSE algorithm is implemented in a method very similar to that of the standard VA. Here, a *joint* state $S_i^{k-1,L} = [s_{i,1}^{k-1,L_1} \; s_{i,2}^{k-1,L_2}]$ is defined by appending the primary ($s_{i,1}^{k-1,L_1}$) and secondary ($s_{i,2}^{k-1,L_2}$) states. Note that in this case, each joint state at time $k-1$ can transition to M^2 states at time k, and can be reached by the same number of states from time $k-2$. Hence, the number of states required to implement the optimal joint VA is $M^{L_1+L_2}$. Complexity reduction techniques originally developed for single-channel MLSE, such as reduced-state sequence estimation (RSSE) [4], can be extended to JMLSE.

4 Joint MAP Symbol Detection (JMAPSD)

The optimal MAP symbol-by-symbol decoding scheme [5] can provide finite-delay decisions of the transmitted symbols. In contrast to MLSE, the single channel MAPSD has the following features: (i) a decoding trellis need not be maintained; (ii) storage of survivor sequences is not required; (iii) a MAP metric, $p(d_i^{k,L}|r^k)$, is maintained for every subsequence of length $L+1$ defined by $d_i^{k,L} = \{d_i(k), d_i(k-1), \ldots, d_i(k-L)\}$.

The basic recursion to calculate the MAP metrics is given by

$$p(d_i^{k,L}|r^k) = \frac{1}{c} p(r(k)|d_i^{k,L}) \sum_{\{j: d_j^{k-1,L} \in d_i^{k,L}\}} p(d_j^{k-1,L}|r^{k-1}) \tag{3}$$

where c is a normalization constant and $p(r(k)|d_i^{k,L})$ is a Gaussian pdf (likelihood). The corresponding detection algorithm was first derived by Abend and Fritchman [5] for *known* channels, and was recently extended to blind equalization for unknown channels [6]. The summation in (3) is performed over the MAP metrics

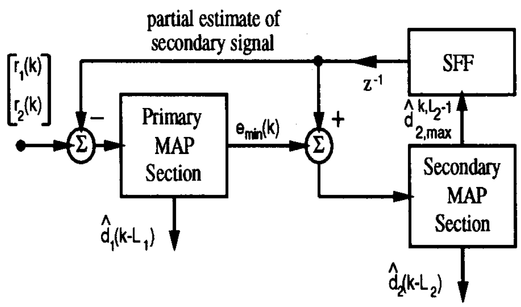

Figure 2: Two-stage JMAPSD algorithm.

of all possible states at time $k-1$ from which state $d_i^{k,L}$ could have been obtained.

The complexity of the single-channel MAPSD algorithm is roughly the same order as that of MLSE. (Note that although MLSE maintains M^L states, it calculates the same number of likelihoods as MAPSD with M^{L+1} subsequences.) The symbol decisions are determined after each iteration using the MAP probability metrics. A suboptimal MAP rule was introduced in [6] to make a decision on the $(k-L)^{th}$ symbol (at time k) as $\hat{d}(k-L) = \hat{d}_i(k-L)$ where

$$\hat{d}_i^{k,L} = \arg \max_{d_i^{k,L}} p(d_i^{k,L}|r^k). \tag{4}$$

We have recently shown in [7] that this decision on symbol $d(k-L)$ can be fed back through a transversal filter in cascade with the MAP estimator, thereby truncating the channel memory seen by the MAP section. This MAP/decision-feedback algorithm provides a performance-complexity tradeoff, ranging from that of the full MAP estimator to the ideal DFE [7].

For cochannel symbol-by-symbol detection, the above MAP algorithm can be readily modified in a manner similar to that of the JMLSE algorithm. This optimal single-stage JMAPSD algorithm (with a complexity on the order of $M^{L_1+L_2+2}$) should provide a BER performance that is comparable to that of JMLSE. However, a computational advantage is obtained when the JMAPSD structure is reconfigured as a *two-stage* algorithm, as illustrated in Figure 2. Here, the first MAP section models the M^{L_1+1} subsequences of the primary channel; the *smallest* residual error $e_{min}(k)$ (i.e., the error corresponding to that subsequence which yields the *maximum* metric at time k) becomes the input of the second MAP section, which models the M^{L_2+1} subsequences of the secondary channel. Hence, the complexity of the two-stage JMAPSD is only on the order of $M^{L_1+1} + M^{L_2+1}$. The assumption here is that the signal to interference ratio (SIR) is sufficiently large such that the primary MAP metrics converge; thus, cancellation of the primary signal component is nearly complete and $e_{min}(k)$ contains only the secondary signal component (plus additive noise).

However, by using a feedback mechanism to subtract a partial estimate of the ISI due to the secondary channel, the two-stage JMAPSD algorithm can also be operated in low-to-medium SIR conditions. This secondary feedback filter (SFF), also shown in Figure 2, uses the suboptimal decisions $\hat{d}_{2,max}^{k,L_2-1}$ obtained from (4) to improve the SIR seen by the first MAP section (see [8] for details). Although the SFF may introduce some error propagation due to decision feedback, for relatively low SIR simulations we obtain a significant improvement in performance.

Table 1: $T/2$-Spaced Channel Coefficients

Primary	Secondary
0.03687 + j0.01069	0.00143 + j0.01187
-0.04924 + j0.01239	0.03958 + j0.02610
-0.07221 - j0.00453	0.10806 + j0.01603
0.07563 - j0.03614	0.13480 - j0.01580
0.14937 - j0.02998	0.06418 - j0.02735
-0.06092 + j0.05171	-0.03438 + j0.00071
-0.26619 + j0.11931	-0.04526 + j0.02663
-0.09562 + j0.02440	0.01293 + j0.01065
0.25408 - j0.20513	0.02962 - j0.01447
0.32938 - j0.34410	-0.00848 - j0.00619
0.13014 - j0.26904	-0.02183 + j0.01307
-0.00265 - j0.11041	0.00265 + j0.00778
0.01960 - j0.02915	0.01088 - j0.00544
0.03387 - j0.01374	0.00000 + j0.00000

5 Computer Simulation Results

The BER performance of these nonlinear cochannel demodulation algorithms was evaluated for binary signaling (BPSK). The primary and secondary channels were obtained from an actual V.32 call setup channel estimation algorithm. The 14 $T/2$-spaced impulse response samples for each channel are listed in Table 1. The noise and interfering signal were specified by SNR = 10 $\log(E_1/N_o)$ and SIR = 10 $\log(E_1/E_2)$, where $E_j = E[d_j^2(k)]$ and $N_o/2$ is the noise spectral density. For the algorithms in this study, $\{E_j\}$ were assumed to be known at the receiver; in particular, $E_1 = 1$ for convenience.

The JMLSE algorithm was implemented with a

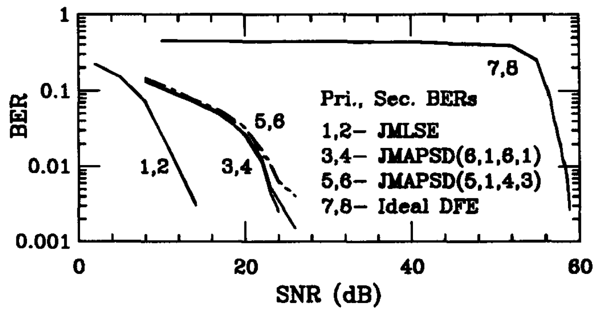

Figure 3: Low SIR condition (SIR = 0 dB).

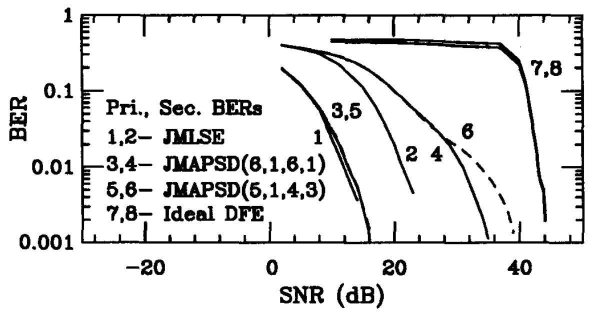

Figure 4: High SIR condition (SIR = 10 dB).

$M^{2L} = 2^{12} = 4096$ joint state VA, and bit decisions were computed after a delay of $4(L+1) = 28$ symbols. Its performance was compared with the two-stage JMAPSD($P_{map}, P_{df}, S_{map}, S_{df}$) algorithm where P_{map} and P_{df} refer to the number of primary (P) channel coefficients modeled by the MAP and DF sections, respectively (similar definitions apply for the secondary (S) channel). For example, JMAPSD(5,1,4,3) is a $2^5 = 32$-state MAP section cascaded with a one-symbol DF filter for the primary channel, and a 16-state MAP section cascaded with a three-symbol DF filter for the secondary channel. As a benchmark, the ideal DFE for cochannel demodulation (which includes a SFF) was also simulated, and its BER was determined with *detected* bits fed back.

From the BER curves in Figure 3 (SIR = 0 dB) and Figure 4 (SIR = 10 dB), we can make the following observations: (i) for low SIRs, JMLSE (or, equivalently, single-stage JMAPSD) provides the best performance; (ii) for high SIRs, two-stage JMAPSD provides nearly the same performance as JMLSE, but at a much lower complexity; (iii) the performance of two-stage JMAPSD always exceeds that of the DFE.

6 Conclusion

Sequence estimation and symbol-by-symbol detection algorithms for the demodulation of cochannel signals have been presented. For known channels, JMLSE and single-stage JMAPSD are optimal techniques for recovering both data streams when their signal energies are comparable (i.e., for low SIR conditions). However, for high SIR conditions, the low complexity two-stage JMAPSD algorithm provides near-optimal performance, far exceeding that of the ideal DFE. Extension of this work to unknown channels (*blind* demodulation) is also possible; the corresponding cochannel blind equalization algorithms are described in [8].

References

[1] S. Verdú, "Recent progress in multiuser detection," In A. Porter and S. C. Kak, editors, *Advances in Communications and Signal Processing*, pp. 27–38, Springer-Verlag, New York, 1989.

[2] R. P. Gooch and B. J. Sublett, "Demodulation of cochannel QAM signals," *Proc. IEEE Int. Conf. Acoustics, Speech, Signal Processing*, pp. 1392–1395, Glasgow, Scotland, May 1989.

[3] J. G. Proakis, *Digital Communications*, McGraw-Hill, New York, 2nd Ed., 1989.

[4] M. V. Eyuboğlu and S. U. H. Qureshi, "Reduced-state sequence estimation with set partitioning and decision feedback," *IEEE Trans. Communications*, vol. 36, pp. 13–20, Jan. 1988.

[5] K. Abend and B. D. Fritchman, "Statistical detection for communication channels with intersymbol interference," *Proc. IEEE*, vol. 58, pp. 779–785, May 1970.

[6] R. A. Iltis, J. J. Shynk, and K. Giridhar, "Recursive Bayesian algorithms for blind equalization," *Proc. Twenty-Fifth Asilomar Conf. Signals, Systems, Computers*, pp. 710–715, Pacific Grove, CA, Nov. 1991.

[7] K. Giridhar, J. J. Shynk, and R. A. Iltis, "Bayesian/decision-feedback algorithm for blind adaptive equalization," *Optical Engineering*, vol. 31, pp. 1211–1223, June 1992.

[8] K. Giridhar and J. J. Shynk, "MAP and ML demodulation algorithms for the joint recovery of cochannel signals," *IEEE Trans. Communications*, submitted 1993.