GAUSSIAN SYMBOLS DETECTION AND FREQUENCY OFFSET ESTIMATOR WITH LOW COMPUTATIONAL COMPLEXITY IN MIMO

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ABSTRACT

A common practice in detection schemes is to consider a relaxation of the discrete problem. The problem of Gaussian symbols detection in MIMO systems in the presence of channel estimation errors. Under this outline computationally efficient approximations of the maximum a posteriori (MAP) detector are developed. The new detectors based on a relaxation of the discrete nature of the digital constellation and on the channel estimation error statistics. This leads to a non-convex program that is solved efficiently via a hidden convexity minimization approach .Additionally by using a Bayesian EM approach, comparable BER performance to that of the MAP detector can be achieved. Next extend the detection scheme to the case where the noise variance is unknown. A modified Bayesian EM approach with annealed Gibbs sampling to perform joint noise variance estimation and symbols detection. Training signal designs based on frequency-domain (FD) and time-domain (TD) are used in the present system, carrier frequency offset (CFO) estimation is obtained with great complexity reduction through factor decomposition for the derivative of the cost function. The CFO estimate's variance and Cramer-Rao bound (CRB) are developed to optimize the parameter of the simplified estimator and also to evaluate the estimation performance.

1. INTRODUCTION

OFDM is becoming a very popular multi-carrier modulation technique for transmission of signals over wireless channels. It converts a frequency-selective fading channel into a collection of parallel at fading subchannels, which greatly simplifies the structure of the receiver. The time domain waveform of the subcarriers are orthogonal (subchannel and subcarrier will be used interchangeably hereinafter), yet the signal spectral corresponding to different subcarriers overlap in frequency domain. Hence, the available bandwidth is utilized very efficiently in OFDM systems without causing the ICI (inter-carrier interference). By combining multiple low-data-rate sub- carriers, OFDM systems can provide a composite high-data-rate with long symbol duration. That helps to eliminate the ISI (inter-symbol interference), which often occurs along with signals of a short symbol duration in a multipath channel.

In the linear Gaussian channel model that we consider in this paper, it is well known that in order to achieve capacity, powerful coding schemes must be combined with shaping methods which result in a near-Gaussian distribution of the symbol's amplitude [3], [4]. Two practical schemes that obtain shaping gain are "trellis shaping" [5] and "shell mapping"[6]. Though theory states that the signal points should be chosen from a continuous Gaussian distribution, in practice, since the constellations are finite this means that optimal gain can not be achieved. In performing constellation shaping, we note that approximating the optimal Gaussian with a discrete distribution can be achieved in many ways. We focus here on the Maxwell-Boltzman (M-B) distribution [7]. The optimal detector for digital constellations can be implemented by using a brute-force approach which searches over all symbol possibilities. Typically this is impractical due to the massive computational burden it presents. Several alternative approaches exist, such as the sphere detector [8] which is optimal, and suboptimal approaches such as semidefinite relaxation [9] and BLAST [10]. The most common class of suboptimal detectors is the class of linear detectors, i.e. the matched filter (MF), the decorrelator or zero forcing (ZF), and the minimum mean-squared error (MMSE) detectors [11].

Here we rely on the work of Wiesel et al. [12]-[13] who considered a frequentist setting and extend it to the Bayesian framework and focus on the MMSE and the maximum a posteriori (MAP) detectors. A common practice in detection schemes, is to consider a relaxation of the discrete problem. The relaxation leads to a continuous optimization problem, that although suboptimal, in many cases provides a tractable optimization problem, that is simpler to solve. The majority of the literature concentrates on the basic case, in which it is assumed that the channel matrix is completely specified [11]. In this setting, the MMSE, Linear MMSE (LMMSE) and MAP estimators coincide and have a simple closed form solution with identical detection performance. In contrast, when a noisy channel estimate is considered, the MMSE, LMMSE and MAP approaches lead to different estimators. In fact, we will show that the solution of the MMSE leads to an intractable integration, whereas the MAP estimator can be efficiently found.

2. RELATED WORK

A. OFDM SYSTEM

OFDM starts with the “O", i.e., orthogonal. That orthogonality differs OFDM from conventional FDM (frequency-division multiplexing) and is the source where all the advantages of OFDM come from.

The input serial binary data will be processed by a data Scrambler first and then channel coding is applied to the input data to improve the BER (bit error rate) performance of the system. The encoded data stream is further interleaved to reduce the burst symbol error rate. Dependent on the channel condition like fading, different base modulation modes such as BPSK (binary phase shift keying), QPSK (quadrature phase shift keying) and QAM are adaptively used to boost the data rate. The modulation mode can be changed even during the transmission of data frames. The resulting complex numbers are grouped into column vectors which have the same number of elements as the FFT size, N. For simplicity of presentation and ease of understanding, we choose to use matrix and vector to describe the mathematical model. Let S(m) represent the m-th OFDM symbol in the frequency domain, i.e., Where m is the index of OFDM symbols. We assume that the complex-valued elements {S (mN); S(mN + 1); : : : ; S(mN + N-1)} of S (m) are zero mean and uncorrelated random variables whose sample space is the signal constellation of the base modulation (BPSK, QPSK and QAM). To achieve the same average power for all

$$S(m) = \begin{pmatrix} S(mN) \\ . \\ S(mN+N-1)_{Nx1} \end{pmatrix} \quad (1)$$

different mappings, a normalization factor KMOD is multiplied to each elements of S (m) such that the average power of the different mappings is normalized to unity.. Let FN be the N-point DFT matrix whose $(p,q)^{th}$ elements is $e^{ij\ 2\pi/N\ (p-1)(q-1)}$. The resulting time domain samples s(m) can be described by

$$S(m) = \begin{pmatrix} S(mN) \\ . \\ . \\ S(mN+N-1)\ _{Nx1} \\ = (1/N)F^{H}_{N}S(m) \end{pmatrix} \quad (2)$$

Compared to the costly and complicated modulation and multiplexing of conventional OFDM systems, OFDM systems easily implement them by using FFT in baseband processing.

MIMO information-theoretic performance bounds in more detail in the next section. Capacity increases linearly with signal-to-noise ratio (SNR) at low SNR, but increases logarithmically with SNR at high SNR. In a MIMO system, a given total transmit power can be divided among multiple spatial paths (or modes), driving the capacity closer to the linear regime for each mode, thus increasing the aggregate spectral efficiency, assumes an optimal high spectral-efficiency MIMO channel (a channel matrix with a flat singular-value distribution), MIMO systems enable high spectral efficiency at much lower required energy per information bit.

B. Capacity

The information-theoretic bound on the spectral efficiency is a function of the total transmits power and the channel phenomenology. In implementing MIMO systems, we must decide whether channel estimation information will be fed back to the transmitter so that the transmitter can adapt. Most MIMO communication research has focused on systems without feedback. A MIMO system with an uninformed transmitter (without feedback) is simpler to implement, and at high SNR its spectral-efficiency bound approaches that of an informed transmitter (with feedback).

One of the environmental issues with which communication systems must contend is interference, either unintentional or intentional. Because MIMO systems use antenna arrays, localized interference can be mitigated naturally. The benefits extend beyond those achieved by single-input multiple-output systems, that is, a single transmitter and a multiple-antenna receiver, because the transmit diversity nearly guarantees that nulling an interferer cannot unintentionally null a large fraction of the transmit signal energy.

3.SYSTEM DESCRIPTION

Consider a flat fading MIMO communication system of M transmits and N receiver antennas. The data stream is multiplexed to M data sub streams and transmitted by M transmit antennas simultaneously. The baseband equivalent model of the received signal vector at the instant of sampling can be represented by

$$Y = H_x + w \quad (3)$$

where $y \alpha \mathbb{C}^{N\times 1}$ is the received vector, $x \in \mathbb{C}^{M\times 1}$ is the transmitted signal vector, and $w \alpha \mathbb{C}^{N\times 1}$ represents the additive noise vector, modeled as a circularly symmetric Gaussian distributed random vector with zero mean and covariance matrix $E\ \{ww^H\} = \sigma^2_w$ I. The (i, j)-th component of the channel matrix $H \in \mathbb{C}^{N\times M}$ represents the channel gain between the j-th transmit and the i-th receive antenna. The input symbol vector x is taken from a (discrete) finite Gaussian distributed signal set D with $E\ \{|xi|^2\} = \sigma^2_x$, $i \in [1, \ldots, M]$. This choice of signal distribution has the property that it reduces the average transmitted power. The notion of (discrete) Gaussian symbols is explained as follows: a continuous Gaussian distribution is quantized into M states of width Δx and the associated discrete probability of the i-th state is given by,

$$P(x_i) = \frac{1}{\sqrt{\pi\sigma_x^2}} \int_{(i-1)\Delta x}^{i\Delta x} \exp\left(\frac{-x^2}{2\sigma_x^2}\right) dx. \quad (4)$$

To achieve this in practice, one resorts to an approximation. The choice we consider in this paper is the M-B distribution, motivated by [14], [15] and [16].

3.1 MIMO System with Imperfect CSI

In most practical cases, the receiver does not have a priori knowledge of the realization of the channel matrix H. In this case, the channel needs to be estimated using a training sequence, i.e. using a set of data symbols, $Xp \in \mathbb{C}^{M\times T}$, which is known to the receiver, where T is the length of the training sequence. Different channel estimation techniques can be employed depending on the prior knowledge about the statistics of H. In case where no a priori knowledge about H exists, the ML channel estimator is $H = Y_p X^H{}_p\ (X_p X\ )^{-1}$, where $Yp \in \mathbb{C}^{N\times T}$ is the observation matrix. The minimal estimation error is achieved when using orthogonal pilot sequence [2] $X_p{}^X H_p = P/M$ I, where P is the total transmitted power for training vectors. Thus the channel matrix can be expressed as

$$H = \hat{H} + \Delta \quad (5)$$

where $\sigma^2 h \triangleq \sigma^2{}_w M/P$. In general, the overall system model for the MIMO system with imperfect CSI can be expressed as

$$Y = Hx + w \quad (6)$$

$$H = \hat{H} + \Delta \quad (7)$$

3.2 Detection in a Mismatched Receiver

In this section review two detection schemes for MIMO symbols ignoring channel uncertainty. In this regard, perform the following:

1) The receiver estimates the channel matrix H from Xp and Yp and produces ˆH.

2) The receiver performs detection of the transmitted symbols using the channel estimate ˆH instead of the true channel matrix H, assuming that the estimate is exact

$$\hat{\mathbf{x}}_{MAP}(\mathbf{y}) = \arg\min_{\mathbf{x}\in\mathbf{D}^M} \left\{ \frac{\left\|\mathbf{y} - \widehat{\mathbf{H}}\mathbf{x}\right\|^2}{\sigma_w^2} + \frac{\|\mathbf{x}\|^2}{\sigma_x^2} \right\}. \quad (8)$$

3.3 Bayesian Detection Under Channel Uncertainty

The Bayesian EM algorithm aims to find iteratively the maximum of the posterior density function of the parameter to be estimated, i.e., MAP parameter estimate, in the presence of nuisance parameters. Interestingly, the BEM algorithm, when applied to the estimation of the frequency-selective Rayleigh fading channel in the presence of unknown data symbols, can exactly be realized by iteratively cross coupling the BCJR algorithm with the fixed interval Kalman smoother (KS) operating on an “averaged” state space model where the averaging is performed over the states of the demodulator trellis [37]. Computing of the model parameters of the “averaged” state space model is, however, very tedious including forward-backward processing of the whole set of symbol APP’s and received signal samples. In addition, the computation of matrix inversion is required at every backward processing step. Furthermore, due to this forward-backward processing requirement, the embedding of the BEM algorithm described in [37] into the existing SISO algorithms does not seem to be feasible.

The optimal and suboptimal detection schemes for the transmitted symbols, based on both the estimated channel matrix ˆH and its estimation error matrix Δ. consider the knowledge of the uncertainty of the channel matrix as part of our system model, and we incorporate this knowledge into the detection formulation. First present the optimal detection scheme and suboptimal linear MMSE receiver for this model. Then present two suboptimal detection schemes with low complexity. The first one finds the global minimum point of the optimization problem using a simple one-dimensional line search. The second method uses the Bayesian Expectation Maximization (BEM) to find a maximum of the posterior.

A novel formulation of the BEM algorithm which avoids the shortcomings due to the “averaged” state space model. As shown in, the BEM algorithm can alternatively be implemented by iteratively cross coupling the BCJR algorithm with a vector Kalman smoother operating on the time-varying state space model given at the i^{th} iteration.

The noise vector V_k has the PDF and it is independent of the noise vector W_k. In many practical cases, the computationally demanding Kalman smoother can be replaced with the KF without deteriorating the symbol or bit error rate of the associated detector significantly.

Contrary to the “averaged” state space model, building of the state space model (38) and (39) does not require any actual processing at all.

On the other hand, the vector KF operating on this state space model requires inversion of matrix at each time step and, thus, it is computationally more demanding than the scalar KF operating on the "averaged" state space model. However, by virtue of the diagonality of the covariance matrix of, the matrix inversions can be avoided and the computational burden of the vector Kalman processing can be significantly alleviated by applying the sequential processing technique outlined in [39]. Specifically, when applying the sequential processing, able to obtain a computationally efficient estimator referred here to as a soft decision directed KF (SDD-KF) which can be described as follows: For each time step, k = 1,….N , compute

$P = P - KA_m^T P$ (9)

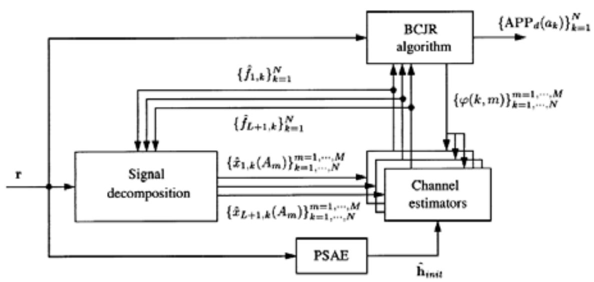

FIG:3.1 The block diagram of the reduced complexity BEM algorithm based on decomposing the received signal into independent multipath components

3.4 Conventional Matched Filter Detector

This is the simplest way to demodulate the received signal: a bank of matched filters, one matched to each user's spreading waveform, is applied to the received signal. Thus, it demodulates all users independent of each other. Consider the first time interval (i = 0) and the jth user,the statistics of the MAI term are different from the noise term and hence it should be treated differently. Specifically,

- Is an in-band interference unlike noise which is wideband
- Cannot be rejected through a band-pass filter

Occurs in different forms in other systems also e.g. Multi-Carrier interference in OFDM. Since the conventional matched filter detector is designed for the case of orthogonal spreading waveforms, it does not take MAI into account.

On applying the same detector to the non-orthogonal case, MAI is treated as a noise term. Thus, correlating the received signal with user j's chip sequence, get

$$y_j = \int_0^{T_b} r(t) s_j(t) dt \qquad (10)$$

$$= A_j b_j + \sum_{\substack{k=1 \\ k\neq j}}^{K} A_k b_k(i) \rho_{kj} + n_j \qquad (11)$$

Hence,=$A_j b_j$ (12)

$$\hat{b}_j = sign(y_j) \qquad (13)$$

Similarly, other users can be demodulated. The conventional matched filter detector

- Is simple to implement
- Does not require knowledge of the channel or the user amplitudes
- Does not take MAI into account and hence gives non-zero probability of error even with zero noise.
- Suffers from the Near-Far Problem. That is, if the amplitude of one user is higher than others, it will cause a high BER in all other users' demodulated data (due to the MAI term). Thus stringent power control is necessary while using the conventional matched filter detector with non-orthogonal codes.

3.5 Optimal MAP Detection

The MAP detector is given by (5), but after considering the channel estimation error, have

P (x) = eN $(0.\sigma^2_x I)$ (14)

where $\sigma^2 h$ is the variance of the channel estimation error, given in (3). As in Section II-B, we make the same assumption on the distribution of **x**. Therefore, the MAP detector can be written as

$$\hat{\mathbf{x}}_{MAP}(\mathbf{y}) = \arg\min_{\mathbf{x}\in\mathcal{D}^M} \left\{ N \log\left(\sigma_h^2 \|\mathbf{x}\|^2 + \sigma_w^2\right) + \frac{\left\|\mathbf{y} - \hat{\mathbf{H}}\mathbf{x}\right\|^2}{\sigma_h^2 \|\mathbf{x}\|^2 + \sigma_w^2} + \frac{\|\mathbf{x}\|^2}{\sigma_x^2} \right\}. \qquad (15)$$

The solution is computationally intensive. Hence, i nvestigate two low complexity suboptimal detectors.

3.5.1 Hidden Convexity Based MAP Detector

Here developed a novel approach for the MAP detector. Suggest relaxing the discrete constraint over x and instead assuming it stems from a continuous Gaussian distribution. Therefore, the detector can be written as

X_D – MAP (y) = Q [Xc – MAP (y)] (16)

where $\mathbf{x}_{C-MAP}$ (**y**) is the solution to the system with a continuous random vector **x** with multivariate Gaussian distribution, resulting in

$$\hat{\mathbf{x}}_{C-MAP}(\mathbf{y}) = \arg\min_{\mathbf{x}\in\mathcal{C}^M} \left\{ N \log\left(\sigma_h^2 \|\mathbf{x}\|^2 + \sigma_w^2\right) + \frac{\left\|\mathbf{y} - \hat{\mathbf{H}}\mathbf{x}\right\|^2}{\sigma_h^2 \|\mathbf{x}\|^2 + \sigma_w^2} + \frac{\|\mathbf{x}\|^2}{\sigma_x^2} \right\}. \qquad (17)$$

Problem (16) is an M-dimensional, nonlinear and nonconvex optimization program. In [32]-[33] the authors presented a method to transform a similar problem into a tractable form which can be solved efficiently. Under this setting, the vector **x** was treated as an unknown deterministic vector. In our setting, the vector **x** is treated as a random Gaussian vector. This difference results in an additional quadratic term in the MAP objective function, namely $\|\mathbf{x}\|2/\sigma^2 x$, which incorporates the a priori information about the random vector **x**. The following theorem shows that this method can also be applied in the MAP problem.

3.5.2 MAP Detector Using Bayesian EM

Provide an alternative solution to the one suggested to provide a comparison. Here develop a detection scheme which is based on the BEM methodology. The BEM methodology is a general technique for finding MAP estimates where the model depends on unobserved latent variables and is based on the classical EM algorithm [40], and is known to converge to a stationary point of the posterior density corresponding to a mode, though convergence to the global mode is not guaranteed, as is well known for the standard EM methodology. This missing data problem is overcome by considering the hidden variables as being random variables and averaging over their distribution.

BEM is best summarized with the following three steps:

1) Initial guess of the parameters.

2) Replace the missing values by their expectations given the guessed parameters (E),

3) Estimate parameters by maximising the expectation (M) Steps (2) and (3) are repeated until convergence. We now provide a solution for finding the MAP estimator of **x** using the BEM method. For this purpose rewrite (4) as

$$Y = G_x + W \qquad (18)$$

where **G** is a Gaussian random matrix with mean ˆ**H** and variance of each element $\sigma^2{}_h$, as defined in (3). At each BEM iteration, the algorithm maximizes the expected log likelihood (with respect to **G**, given **y** and parameterized by **x**). Assume that $\mathbf{x}_n$ is the estimated **x** at iteration n. Then, at iteration $n + 1$, update the estimate as

$$X_{n+1} = (\quad {}_2 (y,x_n) + \sigma^2{}_w/\sigma^2{}_x)^{-1} \quad {}_1 (y,x_n)^T y \qquad (19)$$

To demonstrate this, first using the Kronecker product, we rewrite (23) as

$$Y = (x^T * I)\, g + w \qquad (20)$$

where **g** = **vec**(**G**). The Bayesian MMSE become

$$Eg|y;xn\{g\}=vec(H)+\frac{(x^T * I)\,(y-Hxn)}{\|xn\|\,2+\sigma 2w/\sigma 2h} \qquad (21)$$

$$\mathbf{COV}_{\mathbf{g}|\mathbf{y};\mathbf{x}_n}\{\mathbf{g}\} = \sigma_h^2 I - \frac{\sigma_g^4\,(\mathbf{x}_n\mathbf{x}_n^T \otimes I)}{\sigma_h^2\,\|\mathbf{x}_n\|^2 + \sigma_w^2}. \qquad (22)$$

Initial guess of x_0: Since our problem is non-convex, convergence to the optimal solution is not guaranteed. It is well known that the initial starting point x_0 in such settings will influence whether the solution converges to the optimal solution. As a starting point we suggest to take x_{LMMSE} (Eq. (13)) as the initial guess, and therefore $x_0 = x_{LMMSE}$.

3.5.3 Detection with Unknown Noise Variance Using Annealed Gibbs Sampler

In many practical scenarios, the noise variance σ_w is unknown. Here we derive a novel MAP detection algorithm for model (4) where inference is performed for both **x** and σ^2. To achieve this we need to solve the following

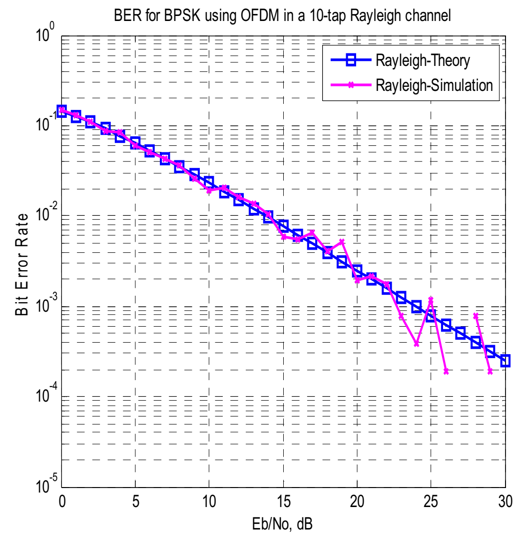

Fig.3.1 Simulation Result of BER Performance BPSK using OFDM Rayleigh channel

$$\left(\widehat{\mathbf{x}}, \widehat{\sigma_w^2}\right) = \underset{(\mathbf{x},\sigma_w^2)}{\arg\max}\, p\left(\mathbf{x}, \sigma_w^2|\mathbf{y}\right). \qquad (23)$$

Before presenting the solution, we note that the BEM approach presented before would be difficult to perform efficiently in the new problem setting, since now the expectation step involves a double integral. An alternative approach which separates the problem into an iterative procedure consisting of the BEM algorithm as before, and a conditional optimization.

Our solution to this problem will be achieved utilizing the concept of annealed Gibbs sampling [40]. The idea is that since we are only after the maximum of the posterior, instead of working with the actual distribution p (**x**, ζ|**y**), we work with a 'heated' version of it. The concept comes from statistical physics, which has become popular in probabilistic optimization theory. When this concept is applied to find the mode of a distribution, one scheme is to consider the target posterior raised to a power, which is analogous to a temperature. As the temperature increases, the mass concentrates on the mode. Asymptotically, as the temperature goes to infinity, the result is a Dirac mass at the mode.

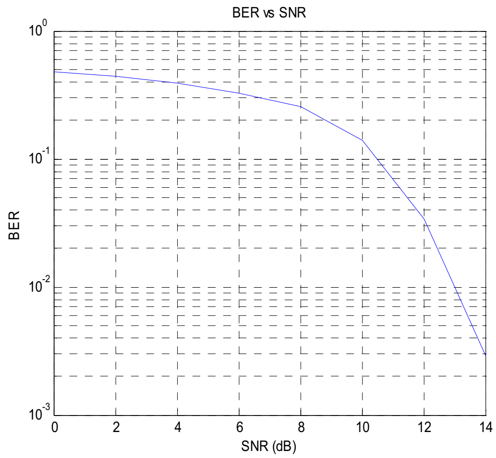

Fig 3.2 Performance of BER Vs SNR

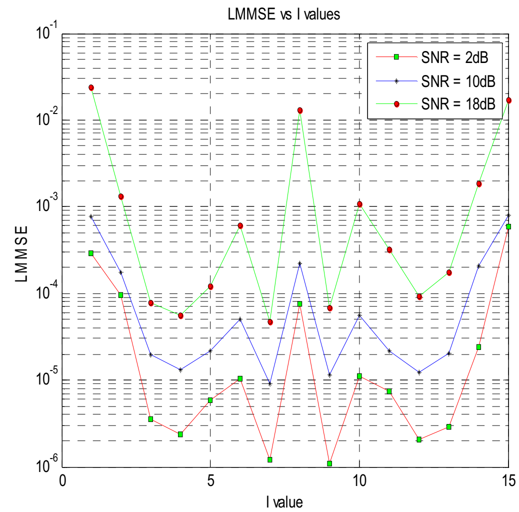

Fig 3.3 Different SNR values of LMMSE

Here adopt a Gibbs sampling approach. This allows us to separate the problem into iterations which involve the original BEM to optimize one of the full conditionals p (x|y, ζ) as before, and the optimization of p (ζ|y, x). Can make an additional computation saving by introducing conjugacy into the model which gives us a parametric full conditional for ζ, with an analytic expression for the mode.

This is a popular choice of prior, since it includes the option of an uninformative prior, and also caters for conjugacy under the Normal Inverse Gamma model [23]. We are free to specify the parameters of the prior as we wish. One way to do this when no a priori information is available is to use a diffuse prior. Specify the parameters of the prior as follows: chosen the shape parameter $\alpha = 2$. Next we center the prior in such a way that it includes some knowledge of the model, whilst remaining diffuse. Set the mean of the Inverse Gamma, given by $E(\zeta) = \beta/\alpha-1$ to be $|x|^2$, leading to $\beta = |x|^2$.

3.5.4 Efficient Implementation and Complexity Analysis

Low complexity implementation of the algorithms developed and discusses their overall complexity. First assess the complexity of the detector presented. The algorithm is composed of two nested line searches. At each iteration of the outer loop (over t) one needs to evaluate the different values of η. This complexity intensive operation can be implemented with low complexity using the following equality

$(H\hat{}H^H + \eta I)^{-1}H\hat{}H = V$ (24)

the overall complexity of the BEM to be

$C_{BEM} = c_{BEM}\, IT_{BEM} = 8/3\, N^3 ITR_{BEM}$ (25)

where ITR_{BEM} is the number of iterations required for convergence. ITR_{BEM} is a random variable which depends on the values of $\sigma^2{}_w$, $\sigma^2{}_h$ and $\mathbf{x}_0$ and therefore, the complexity of the BEM is random and can be only evaluated via simulations. Simulations show that the algorithm converges in less than 10 iterations, depending on $\sigma^2{}_h$ and $\sigma^2{}_w$.

4.CONCUSION

The detection in MIMO systems of near-Gaussian constellations under imperfect channel estimation. Derived the MAP estimator and provided an efficient method for finding it by transforming the multidimensional, nonlinear and nonconvex problem into a simple tractable form. A detection scheme for near Gaussian-digitally modulated symbols with linear complexity, based on the new MAP estimator. Also presented a detection scheme based on the Bayesian EM methodology for the case that the noise variance is unknown a-priori. Simulation results show the improved performance offered by our new approach in comparison to the LMMSE methods in terms of BER.

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