ML Detection for MIMO Systems under Channel Estimation Errors

Fathurrahman Hilman, Jong-Hyen Baek, Eun-Kyung Chae, and Kyungchun Lee

Abstract

In wireless communication systems, the use of multiple antennas at both the transmitter and receiver is a widely known method for improving both reliability and data rates, as it increases the former through transmit or receive diversity and the latter by spatial multiplexing. In order to detect signals, channel state information (CSI) is typically required at the receiver; however, the estimation of CSI is not perfect in practical systems, which causes performance degradation. In this paper, we propose a novel maximum likelihood (ML) scheme that is robust to channel information errors. By assuming a bound on the total power of channel estimation errors, we apply an optimization method to estimate the instantaneous covariance of channel estimation errors in order to minimize the ML cost function. To reduce computational complexity, we also propose an iterative sphere decoding scheme based on the proposed ML detection method. Simulation results show that the proposed algorithm provides a performance gain in terms of error probability relative to existing algorithms.

Keywords

MIMO, Maximum Likelihood Detection, Sphere Decoding, Channel Estimation Error

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I. INTRODUCTION

Multiple-input multiple-output (MIMO) systems in wireless communications employ multiple antennas at both the receiver and transmitter to improve overall system performance in terms of higher data rates and reliability over single antenna systems with the same bandwidth and total power [1]. Higher data rates can be achieved by exploiting multiple independent channels between the transmitter and receiver in order to send multiple data streams, while higher reliability can be attained by sending signals that carry copied information through these channels, allowing the reception of replicated signals at the receiver.

To properly detect signals, channel state information (CSI) is required at the receiver. The CSI can be obtained by employing estimation techniques such as training-symbol based estimation [2], [3] or blind channel estimation [4]–[6]. However, any estimation performed at a receiver will not be perfect in practice, and therefore, estimation errors are inevitable. Such channel estimation errors may cause performance degradation in the signal detector. Well-known techniques for detecting transmitted symbols at MIMO receivers include maximum likelihood (ML), zero forcing (ZF), and minimum mean square error (MMSE) schemes [7]. In terms of error probability, ML detection is optimal; however, conventional ML receivers assume perfect CSI at the receiver.

In this paper, we consider the effects of channel estimation errors on the performance of ML receivers in a MIMO system, an effort that follows previous research in this area. In [8], the authors proposed a robust ML method based on worst-case performance optimization that utilizes the CSI error bound. In [9], a robust decoder was proposed in which knowledge of the variance of channel information errors is taken into account. In [10], [11], a robust decoders for space-time coding that consider channel estimation errors were proposed. In this paper, we propose a novel robust ML detection that exploits the channel estimation error bound. The proposed ML detector finds the instantaneous error covariance matrix that minimizes the ML cost function for each symbol candidate. As this requires high computational complexity, which makes the method impractical for use at higher modulation orders or with a large number of antennas, we derive a suboptimal algorithm based on sphere decoding (SD).
The remainder of this paper is organized as follows. In Section II, we formulate a system model of a MIMO system that accounts for the CSI error. We then propose robust ML and SD systems in Sections III and IV, respectively. In Section V, we show the results of simulations used to evaluate the performance of these systems, and finally, we provide a conclusion in Section VI.

Notation: Lowercase, boldface lettering denotes column vectors. Capital, boldface lettering denotes matrices. The symbols $(.)^T$ and $(.)^H$ represent the transpose and conjugate transpose operations, respectively. The symbol $\|\cdot\|$ indicates the Euclidian norm ($L_2$-norm). $I_M$ denotes an identity matrix of dimensions $M \times M$.

II. SYSTEM MODEL

We model a MIMO system with $N$ and $M$ transmit and receive antennas, respectively. We assume that the antennas at both the transmitter and receiver are separated enough to ensure that there are $M \times N$ independent channels between the transmitter and the receiver.

The received signal at time $t$ can be expressed as

$$y(t) = Hx(t) + n(t),$$

where $x = [x_1, x_2, ..., x_N]^T$ denotes the transmitted signals, $n = [n_1, n_2, ..., n_M]^T$ denotes the noise signals, and $y = [y_1, y_2, ..., y_M]^T$ represents the received signals. The noise vector $n$ is assumed to be a zero-mean complex Gaussian random variable with covariance $\sigma_n^2I_M$. The channel matrix $H$ is an $M \times N$ matrix ($M \geq N$) consisting of complex Gaussian random elements. In the remainder of this paper, the time index $t$ will be omitted for simplicity.

An estimate of the channel matrix $\hat{H}$ is corrupted by estimation errors available at the receiver. The exact channel $H$ can be expressed as $H = \hat{H} + \Delta$, where the error matrix $\Delta$ contains independent random elements having zero mean. We assume that $\Delta$ is independent of both the transmitted symbol $x$ and the channel matrix $H$ as in $[9]$, $[12]$. Then, (1) can be rewritten as

$$y = (\hat{H} + \Delta)x + n = \hat{H}x + \Delta x + n = \hat{H}x + \tilde{n},$$

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where \( \tilde{n} = \Delta x + n \) is the equivalent noise vector.

On the basis of the central limit theorem, for a sufficiently large \( N \), \( \Delta x \) can be approximately modeled as a Gaussian random vector with zero mean and a covariance matrix given by

\[
R_{\tilde{n}} = \mathbb{E}[\tilde{n}\tilde{n}^H] = \mathbb{E}[(n + \Delta x)(n + \Delta x)^H] = \sigma_n^2 I_M + \sigma_x^2 R_{\Delta},
\]

(3)

where \( \sigma_n^2 = \mathbb{E}[|x_k|^2] \) denotes the average signal power, and \( R_{\Delta} = \Delta \Delta^H \). Again, when \( N \) is sufficiently large, the off-diagonal elements of \( R_{\Delta} \) can be ignored, and \( R_{\Delta} \) can be approximated as a diagonal matrix. Hence, \( R_{\tilde{n}} \) also becomes an approximately diagonal matrix. In this paper, we employ the assumption that total channel error power has an upper bound \( E \), i.e., \( \sum_{i=1}^{M} \varepsilon_i \leq E \), where \( \varepsilon_i \) denotes the \( i \)th diagonal element of \( R_{\Delta} \) as in [13].

III. ML DETECTION UNDER CHANNEL ESTIMATION ERROR

Using (3), we can express the ML detection rule as

\[
\hat{x} = \arg \max_{x, R_{\Delta}} \frac{1}{\pi^N \det(R_{\tilde{n}})} \exp \left( -\frac{1}{2} (y - \hat{H}x)^H R_{\tilde{n}}^{-1} (y - \hat{H}x) \right).
\]

(4)

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\]

(4)

Under the assumption that \( \det(R_{\tilde{n}}) \) is approximately equal for all \( R_{\Delta} \), the log-likelihood form of (4) is simplified to

\[
\hat{x} = \arg \min_{x, R_{\Delta}} (y - \hat{H}x)^H R_{\tilde{n}}^{-1} (y - \hat{H}x).
\]

(5)

as in [8].

We define \( \alpha_i \) as the \( i \)th element of vector \( (y - \hat{H}x) \) to simplify the notation. Then, for a given \( x \), (5) becomes

\[
\min_{R_{\Delta}} (y - \hat{H}x)^H R_{\tilde{n}}^{-1} (y - \hat{H}x) = \min_{R_{\Delta}} \sum_{i=1}^{M} \frac{|\alpha_i|^2}{\sigma_n^2 + \sigma_x^2 \varepsilon_i},
\]

(6)

as in [9]. The minimum of (6) can be obtained by applying Cauchy–Schwarz inequality,

\[
\sum_{i=1}^{M} \left( \frac{\sqrt{\sigma_n^2 + \sigma_x^2 \varepsilon_i}}{\sigma_n^2 + \sigma_x^2 \varepsilon_i} \right)^2 \sum_{i=1}^{M} \left( \frac{|\alpha_i|}{\sqrt{\sigma_n^2 + \sigma_x^2 \varepsilon_i}} \right)^2 \geq \left( \sum_{i=1}^{M} |\alpha_i| \right)^2,
\]

(7)
which can be written as
\[
\sum_{i=1}^{M} \frac{|\alpha_i|^2}{\sigma_n^2 + \sigma_x^2 \varepsilon_i} \geq \left( \sum_{i=1}^{M} |\alpha_i| \right)^2 \frac{1}{\sum_{i=1}^{M} (\sigma_n^2 + \sigma_x^2 \varepsilon_i)}.
\] (8)

Under the constraint \(\sum_{i=1}^{M} \varepsilon_i \leq E\), the right-hand side of (8) has the minimum value when
\[
\sum_{i=1}^{M} \varepsilon_i = E.
\] (9)

Therefore, (8) can be rewritten as
\[
\sum_{i=1}^{M} \frac{|\alpha_i|^2}{\sigma_n^2 + \sigma_x^2 \varepsilon_i} \geq \frac{\left( \sum_{i=1}^{M} |\alpha_i| \right)^2}{\sigma_n^2 M + \sigma_x^2 E}.
\] (10)

Each \(\varepsilon_i\) can be obtained by considering the condition of equality in the Cauchy–Schwarz inequality. According to [14], the equality holds when the ratio of each element in the first series of (7) to the corresponding element in second series is constant. More specifically, the equality in (8) is satisfied when
\[
\sqrt{\sigma_n^2 + \sigma_x^2 \varepsilon_i} = \frac{|\alpha_i|}{\sqrt{\sigma_n^2 + \sigma_x^2 \varepsilon_i}},
\] (11)

which results in
\[
\varepsilon_i = \frac{1}{\sigma_x^2} \left( c |\alpha_i| - \sigma_n^2 \right),
\] (12)

where \(c\) is a constant value.

Substituting (12) into (9), we obtain
\[
\sum_{i=1}^{M} \frac{1}{\sigma_x^2} (c |\alpha_i| - \sigma_n^2) = E.
\] (13)

Then by simplifying (13), \(c\) can be expressed as
\[
c = \frac{\sigma_n^2 M + \sigma_x^2 E}{\sum_{i=1}^{M} |\alpha_i|}.
\] (14)

By substituting (14) into (12), we get
\[
\varepsilon_i = \frac{\sigma_n^2 M + \sigma_x^2 E}{\sigma_x^2 \sum_{i=1}^{M} |\alpha_i|} \frac{\sigma_n^2}{\sigma_x^2} - \frac{\sigma_n^2}{\sigma_x^2},
\] (15)

which is the \(i\)th diagonal element of \(R_\Delta\). The estimate of the channel error power \(\varepsilon_i\) in (15) satisfies the equalities in (8) and (10), which implies that the minimum value of (6) is achieved.
We denote $R_\Delta$ that minimizes (6) for a given $x$ as $R_{\Delta,x}$. Finally, by defining $R_{\tilde{n},x} = R_n + \sigma_x^2R_{\Delta,x}$, the ML detector can be expressed as

$$\hat{x} = \arg \min_x (y - \hat{H}x)^HR_{\tilde{n},x}^{-1}(y - \hat{H}x).$$

(16)

IV. SD UNDER CHANNEL ESTIMATION ERROR

A. SD for Colored Noise

In this section, we will briefly describe the conventional SD algorithm and then explain how to apply it to the proposed robust ML detection. As the ML detection scheme has exponential complexity, SD based on the Fincke–Pohst algorithm [15] can be employed in order to implement it practically. SD is typically derived in a real domain system [16], [17]. We will assume a real domain representation for each matrix that can be obtained by using the transformation specified in [17] in the remainder of this section.

We observe that

$$(y - Hx)^TR_n^{-1}(y - Hx) = (x - \bar{x})^TH^TR_n^{-1}H(x - \bar{x})$$

$$+ y^T(R_n^{-1} - R_n^{-1}H(H^TR_n^{-1}H)^{-1}H^TR_n^{-1})y,$$

(17)

where $\bar{x} = (H^TR_n^{-1}H)^{-1}H^TR_n^{-1}y$, and $R_n$ indicates the covariance matrix of the effective noise. Let $U$ be an $N \times N$ upper triangular matrix chosen such that $U^TU = H^TR_n^{-1}H$. We can obtain $U$ by using Cholesky factorization. As the second term in (17) does not depend on $x$, ML detection can be expressed as

$$\hat{x} = \arg \min_x (x - \bar{x})^TU^TU(x - \bar{x}).$$

(18)

The SD avoids exhaustive searches by examining only those points that lie inside of the sphere

$$(x - \bar{x})^TU^TU(x - \bar{x}) \leq d^2,$$

(19)

where $d$ is the sphere radius. After carrying out this transformation, the remainder of the algorithm described in [16], [18] can be followed.
B. Iterative Sphere Decoding

The SD algorithm finds \( \hat{x} \) by using layer-by-layer operations. Hence, SD cannot be directly applied in the proposed ML detection method by merely substituting \( R_n \) with \( R_{\hat{n},x} = R_n + \sigma_x^2 R_{\Delta,x} \) into (17) because \( R_{\Delta,x} \) is a function of \( x \). To overcome this problem, we propose an iterative SD scheme in which we exploit the SD method described in [9] to obtain an initial \( \hat{x} \) to find \( R_{\Delta,x} \) and then perform several iterations to update \( R_{\Delta,x} \) as well as the solution candidates for \( \hat{x} \). Defining \( \hat{x}^k \) as the solution of \( x \) at the \( k \)th iteration, the proposed iterative sphere decoding scheme is summarized as follows:

1) Initialization. \( k \leftarrow 0 \) and find \( \hat{x}^0 \).
2) Calculate \( R_{\Delta,\hat{x}^k} \).
3) Apply the SD algorithm to find \( \hat{x}^{k+1} \).
4) If \( \hat{x}^{k+1} = \hat{x}^k \), then stop. Otherwise, go to the next step.
5) \( k \leftarrow k + 1 \). Go back to step 2.

In step 1, the SD in [9] is applied to find an initial solution \( \hat{x}^0 \). In this step, we can exploit other detectors such as ZF and MMSE as well as successive interference cancellation (SIC) to derive the initial solution. In step 2, we use (12) and (14) to find \( R_{\Delta,\hat{x}^k} \) which denotes \( R_{\Delta,x} \) when \( x = \hat{x}^k \). Then, in step 3, \( R_n \) in (17) is substituted into \( \sigma_n^2 I_M + \sigma_x^2 R_{\Delta,\hat{x}^k} \) in order to apply SD to obtain the solution \( \hat{x}^{k+1} \). However, this solution may not be optimal, as we estimate \( R_{\Delta,x} \) using the value of \( \hat{x}^k \) obtained in the previous iteration. In step 4, the algorithm checks whether \( \hat{x}^k \) is equal to \( \hat{x}^{k+1} \). If so, the algorithm stops, and we set \( \hat{x} = \hat{x}^k \); otherwise, it continues on to the next iteration. We observe that in the proposed SD, a higher number of iterations provide better detection results but also increases the computational complexity.

V. Simulation Results

A. Upper Bound of Total Channel Estimation Error Power is Known

In this subsection, we examine a case in which the upper bound of the total power of channel estimation errors, \( E \), is known at the receiver. We assume that \( \sum_{i=1}^M \varepsilon_i \) has a uniform distribution.
between 0 and $E$. The channel information errors are generated randomly and then normalized to satisfy the constraint of $\sum_{i=1}^{M} \varepsilon_i = 1$. The elements of $H$ are assumed to be independent complex Gaussian random variables with unit variance. We use the formula in [16] to find the initial radius of the proposed SD; specifically, the initial value of $\varepsilon$ is set to 0.1 and then successively decreased to 0.1 times its previous value, which results in a larger radius, until the algorithm finds a solution candidate. The minimum value of $\varepsilon$ is set to $10^{-5}$. If the algorithm still fails to find a solution candidate, the solution is assigned to a specific candidate.

We compare the BER versus the signal-to-noise ratio (SNR) performance of the proposed robust ML detector (16) and SD with those of the ML detector and SD in [9]. The conventional ML detector is included as a BER upper bound, while the conventional ML detector under the perfect CSI assumption is included as a BER lower bound. We consider the performance after the first, second, and fourth iterations of the proposed SD. The proposed SD with optimal $R_{\Delta,x}$, which is obtained by using (14) and (16) in the proposed ML detector, is included as the proposed SD BER lower bound (LB). The ML detector and SD in [9] assume that the variance of the channel estimation error is known at the receiver. Assuming a uniform distribution between $a$ and $-a$, the variance of the channel estimation error is calculated as $(a - (-a))^2 / 12 = a^2 / 3$, where $a$ is the normalized bound value of the channel estimation error.

Figs. 1 and 2 show BER performance comparisons for $2 \times 2$ MIMO systems with $E = 0.9$ and $E = 1.25$, respectively, when QPSK signaling is used. In Fig. 1, it can be seen that the proposed ML detector has SNR gains of 0.6- and 2.3-dB over the ML detector in [9] at BERs of $5 \times 10^{-4}$ and $2 \times 10^{-4}$, respectively. Furthermore, the proposed SD provides 1.2-, 1.9-, and 2.5-dB SNR gains over the SD in [9] at a BER of $5 \times 10^{-4}$ after the first, second, and fourth iterations, respectively. Fig. 2 also shows that the proposed ML and SD schemes outperform those in [9] for $E = 1.25$.

In Section III, we assumed that the size of $\Delta$ is large enough to allow $R_{\Delta}$ to become approximately diagonal; however, it can be seen in Figs. 1 and 2 that, even when the size of $\Delta$ is small, i.e. $N = 2$, the proposed ML detector has an SNR gain relative to [9].
We also note that the proposed SD requires higher computational complexity than the SD in [9], as it performs SD procedures multiple times. However, even at the first iteration (in which SD is only performed twice, including the initial search to find \( \hat{x}^0 \)), the proposed SD outperforms SD in [9]. Furthermore, upon further iteration, the proposed SD provides significant gains over the SD in [9].

Fig. 3 shows the BER performance for \( 2 \times 2 \) MIMO systems with 16-QAM signaling at \( E = 0.9 \). It can be seen that the proposed ML detector has an SNR gain of 0.7 dB over the ML in [9] at a BER of \( 10^{-2} \), while the proposed SD provides 1.3-, 1.8-, and 2.5-dB SNR gains over the SD in [9] after the first, second, and fourth iterations, respectively.

Fig. 4 characterizes the BER performance for \( 4 \times 4 \) MIMO systems with QPSK signaling at \( E = 1.75 \). In this case, the proposed ML detector and SD still outperform the ML detector and SD, respectively, in [9].

**B. Upper Bound of Total Channel Estimation Error Power is Unknown**

In this subsection, we examine the channel estimation errors that follow a Gaussian distribution with zero mean and variance \( \sigma_e^2 \) in cases the upper bound of the total power of channel estimation error, \( E \), is unknown. The remaining assumptions are similar to those in the preceding subsection.

Fig. 5 shows the performance of several detection methods for \( 4 \times 4 \) MIMO systems using QPSK signaling with Gaussian channel estimation errors with a variance of 0.2. As Gaussian channel estimation errors are assumed, an error bound does not exist, but to apply the proposed ML and SD schemes, \( E \) is set to 1.9 at the receiver. At a BER of \( 3 \times 10^{-4} \), the proposed SD provides 1.1-, 1.6-, and 2.2-dB SNR gain over the SD in [9] after the first, second, and fourth iterations, respectively. It is also apparent that the proposed ML detector has an SNR gain of 1.6 dB over the ML detector in [9] at a BER of \( 10^{-4} \).

As the ML criterion depends on both \( x \) and \( R_\Delta \), we need to find \( R_\Delta \) that minimizes the cost function (5) for each symbol candidate to find the optimal solution. The proposed algorithms find an estimate of the instantaneous covariance matrix of channel estimation errors for each detected...
symbol, i.e., $\mathbf{R}_{\Delta, x}$, while the algorithms in [9] only employ long-term statistical information of channel estimation errors. Therefore, the proposed schemes provide better solutions that minimize (5), which results in improved performance even with unbounded Gaussian errors.

C. Total Channel Estimation Error Power is Not Fixed

In the previous two subsections, we considered a high-mobility environment in which the channel estimation error is almost fixed regardless of the SNR. In this subsection, we examine the case where the channel estimation error power is not fixed, i.e., it is changing according to the SNR.

Fig. 6 shows the BER performance comparison for $2 \times 2$ MIMO systems using QPSK signalling when the upper bound of the channel estimation error power is ten times higher than the noise power. Under this assumption, the channel estimation error power decreases as the SNR increases. At a BER of $3 \times 10^{-4}$, the proposed ML detector gives 1.3 dB SNR gain over the ML detector in [9]. Meanwhile, at the same BER level, the proposed SD provides 1.1-, 1.6-, and 2.2-dB SNR gains over the SD in [9] after the first, second, and fourth iterations, respectively.

D. Complexity Comparison

In this subsection, we examine the complexity of the proposed schemes by counting the average number of node visits. At the first iteration, the proposed SD performs two SD procedures, including an initial search to find $\hat{x}_0$, as explained in section IV-B. However, as the radius value of the initial solution is used as the initial search radius at the first SD iteration, its complexity can be less than twice the complexity of the SD in [9], which requires only one SD iteration. Similarly, the radius of the solution at each iteration is used as the initial radius at the next iteration in order to reduce the computational complexity. Furthermore, the proposed SD terminates the iteration process if the solution from the previous iteration is equal to the solution of the current iteration, which results in an overall complexity reduction.

Fig. 7 shows the average number of node visits for $2 \times 2$ MIMO systems. At an SNR of 18 dB at which the BERs are approximately $10^{-2}$, the average number of node visits of the
proposed SD after the first, second, and fourth iterations is only 1.31, 1.68, and 2.05 times higher, respectively, than that of the SD in [9] when 16QAM signaling is used. In addition, the number of node visits is only 1.33, 1.71, and 2.15 times higher after the first, second, and fourth iterations, respectively, when QPSK signalling is used at the same SNR. Furthermore, the complexity gap between the proposed SD and the SD in [9] is reduced at higher SNRs.

VI. CONCLUSION

In this paper, a novel ML detection algorithm for MIMO systems that is robust to channel estimation errors has been proposed. This scheme minimizes the ML cost function by estimating the instantaneous covariance of channel information errors, which is accomplished by applying an optimization method that assumes knowledge of the channel information errors bound. In light of the high computational complexity of ML detection schemes, an SD scheme based on the proposed ML detection has also been proposed; this scheme applies multiple SD iterations in which both the covariance of the channel estimation errors and the solution candidate are updated in order to find an optimal solution. In the system model, it is assumed that the number of transmit antennas \( N \) is large enough to ensure that the instantaneous covariance is an approximately diagonal matrix and that the central limit theorem can be applied. However, simulation results have shown that, even for \( N = 2 \), the proposed ML detection scheme outperforms the ML detection in [9] in terms of the BER. It has also been observed that the proposed SD provides an SNR gain relative to the SD in [9] after the first iteration.

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Fig. 1. BER vs. SNR for $2 \times 2$ MIMO systems, QPSK, and $E = 0.9$
Fig. 2. BER vs. SNR for $2 \times 2$ MIMO systems, QPSK, and $E = 1.25$
Fig. 3. BER vs. SNR for $2 \times 2$ MIMO systems, 16-QAM, and $E = 0.9$
Fig. 4. BER vs. SNR for $4 \times 4$ MIMO systems, QPSK, and $E = 1.75$
Fig. 5. BER vs. SNR for $4 \times 4$ MIMO systems, QPSK, and Gaussian channel estimation errors with $\sigma^2_e = 0.2$. 

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Fig. 6. BER vs. SNR for $2 \times 2$ MIMO systems, QPSK. The upper bound of the channel estimation error power is assumed to be ten times higher than the noise power.
Fig. 7. Average number of node visits vs. SNR for $2 \times 2$ MIMO systems, various modulation schemes, and $E = 0.9$