Adaptive Modulation for ED-Based Non-Coherent Massive SIMO Systems

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This work was supported by the National Natural Science Foundation (NSF) of China under Grant 61771197.

ABSTRACT Link adaptation in coherent wireless communications has sparked great research enthusiasm. However, adaptive techniques are equally important for non-coherent counterparts although relatively less attention has been dedicated to. This letter studies the adaptive modulation for the energy detection (ED)-based non-coherent systems. Specifically, we consider a massive single-input multiple-output (SIMO) network, where a single-antenna user communicates with a base station (BS) with tens/hundreds of antennas. In particular, an optimization problem is formulated in order to find the signal-to-noise ratio (SNR) switching thresholds that maximize the average spectral efficiency (ASE). After deriving the SNR distribution and symbol error rate (SER), this problem is solved by applying the Lagrangian method. With switching thresholds, rate and power adaptation are made based on the instantaneous SNR. Numerical results indicate for the proposed scheme, there exists a trade-off between the target SER and ASE. That is, the ASE falls if one wishes to reduce the target SER. Under this circumstance, mounting more antennas can avoid the loss in ASE.

INDEX TERMS Non-coherent communications, massive SIMO systems, energy detection, SNR switching thresholds, average spectral efficiency, nonnegative PAM.

I. INTRODUCTION

Massive multiple-input multiple-output (MIMO) system, where a large number of antennas are deployed at base stations (BSs) to serve a relatively small number of users sharing the same frequency resources, has recently received a great deal of interest due to its huge potential gains [1]. For example, massive MIMO is energy efficient as the transmit power scales down with the number of antennas at the BS. Meanwhile, channel vectors associated with different users are asymptotically orthogonal, thus both intra- and inter-cell interference can be eliminated with simple detection or precoding algorithms [2]. To reap these benefits, channel state information (CSI) is required at base station (BS). However, acquiring CSI needs the use of pilot sequences, which can cause pilot contamination if the same set of pilots is reused across cells [3]. Besides, channel estimation would greatly increase complexity and power consumption of the front-haul infrastructure [4]. Alternatively, architectures that use simple, robust and energy efficient designs are attractive to realize the benefits provided by large antenna systems [5].

As a promising alternative, non-coherent communications systems require no knowledge of instantaneous CSI at either the transmitter or receiver. Until recently, energy detection (ED)-based non-coherent massive single-input multiple-output (SIMO) systems prove to be promising and draw much attention [6]. By using large antenna arrays, ED-based receiver could operate without explicit knowledge of the CSI, as signal squaring and averaging performed over receive antennas provides a good estimate of the channel energy [7]. Besides, for general channel fading statistics, the performance of ED-based non-coherent SIMO communication is the same, in a scaling law sense, as that of the coherent scheme with perfect CSI [8].

In the meanwhile, link adaptation is widely acknowledged to be effective to enable robust transmission over time-varying channels [9]. Motivated by the above, the combination of massive MIMO and link adaptation has emerged as a promising option to further enhance the spectral efficiency. A low-complexity multiuser adaptive modulation scheme was proposed for uplink massive MIMO systems,
which requires slow-varying large-scale shadowing information for the users [10]. Link adaptation in massive MIMO was analyzed from the perspective of throughput-fairness trade-off in [11]. Authors in [12] proposed an adaptive modulation scheme which utilizes a lookup table as an index of the modulation type by using the feature of amplitude beam selection. More recently, a learning-based rate adaptation mechanism was proposed for a downlink massive MIMO with underlaid device-to-device links [13]. An adaptive modulation model based on machine learning suitable for 5G NR was introduced in [14], where the correlation of channels between antennas was incorporated. In [15], an adaptive streaming for massive MIMO networks by employing approximate Markov decision process and reinforcement learning, where the dynamics of user arrivals and departures are considered.

Apart from coherent systems, we emphasize that the adaptive modulation is equally important in non-coherent counterparts. Without adaptation, non-coherent systems have to be designed for the worst-case channel conditions, which can severely degrade the spectral efficiency/error performance [16]. As such, this letter addresses the adaptive modulation for ED-based non-coherent massive SIMO systems. First, an optimization problem is formulated to find switching thresholds of signal-to-noise ratio (SNR) that maximize the average spectral efficiency (ASE). Given the derived SNR distribution and symbol error rate (SER) expressions, these thresholds are obtained by solving this problem. Afterwards, rate and power adaptation are performed according to the instantaneous SNR.

The remainder of this paper is organized as follows. The system model and problem formulation are described in Section II. The parametric analysis of SNR distribution and SER expression is detailed in Section III, where perfect CSI is assumed. In Section IV, we present the adaptive modulation for ED-based non-coherent massive SIMO systems. Computer simulations are undertaken to demonstrate the effectiveness of the proposed scheme in enhancing the average spectral efficiency in Section V. Finally, concluding remarks are drawn in Section VI.

Notation: $\mathbb{C}^{n \times m}$ indicates a complex matrix of size $n \times m$. Bold variables represent matrices and vectors. Random variable $x \sim \mathcal{N}(\mu, \sigma^2)$ denotes a complex Gaussian distribution with mean $\mu$ and variance $\sigma^2$, while $x \sim \mathcal{N}(\mu, \sigma^2)$ indicates the real Gaussian distribution. $\Re\{\cdot\}$ and $\Im\{\cdot\}$ denote the real and imaginary parts of the argument. $(\cdot)^H$, $(\cdot)^T$ and $(\cdot)^*$ refer to the transpose, conjugate transpose and complex conjugate operators, respectively. $[\mathbf{a}]_m$ represents the $m$-th element of vector $\mathbf{a}$. For convenience, the key notations in this paper are summarized in Table 1.

### II. SYSTEM MODEL AND PROBLEM FORMULATION

#### A. ED-BASED NON-COHERENT MASSIVE SIMO SYSTEMS

We consider a system including a single-antenna user and a base station (BS) with $M$ antennas, where the user transmits signals to the BS. Basically, this configuration is equivalent to a diversity reception system with $M$ branches. Based on this system setup, the $M \times 1$ received signal vector is

$$y = \sqrt{P_{ts}}h\mathbf{x} + n,$$

where $x$ is drawn from a non-negative pulse amplitude modulation (PAM) constellation $P = \{\sqrt{P_1}, \sqrt{P_2}, \ldots, \sqrt{P_K}\}$, with $K$ being the constellation size. The elements of $h$ obeys the complex Gaussian distribution with zero mean and variance $\sigma_n^2$, i.e., $\mathcal{CN}(0, \sigma_n^2)$, $n$ is the additive gaussian noise vector with elements obeying $\mathcal{CN}(0, \sigma_n^2)$. In this study, the channel and noise are supposed to be mutually independent. After the received signal vector being filtered, squared and integrated, the average power across all antennas is represented by [18]

$$z = \frac{1}{M} \mathbf{y}^H \mathbf{y} = \frac{P_{ts}}{M} h^H \mathbf{x}^2 + \frac{2\sqrt{P_{ts}}}{M} \Re\{h^H n\} x + \frac{1}{M} n^H n$$

$$M \rightarrow \infty \quad \Rightarrow \quad \frac{P_{ts}}{M} h^H \mathbf{x}^2 + \frac{1}{M} n^H n \approx \frac{P_{ts}}{M} h^H x^2 \sigma_n^2 + \sigma_n^2$$

(2)

Given the knowledge of $\sigma_n^2$ and $\sigma_n^2$, the receiver can recover $x$ based on (2). Since $M$ is finite in practice, then depending on which symbol was transmitted, $z$ approximates to one of $K$ Gaussian variables. As an example, with a 4 non-negative PAM, the probability density function (PDF) of $z$ over an additive white Gaussian noise (AWGN) channel is shown in Fig. 1. From this figure, four distinct Gaussian-like curves are observed, corresponding to four constellation points. Accordingly, the positive line is partitioned into multiple decoding regions with boundaries $[d_k]_{k=0}^K$ to decide which symbol was transmitted based on the observation of $z$, i.e.

$$\hat{x} = \sqrt{P_{ts}}, \quad \text{if} \quad d_{k-1} \leq z < d_k.$$  

(3)

1 In the case of multiple users, the multiuser interference will significantly degrade the SER performance. To address this problem, we have developed an efficient way to design a joint multi-user constellation for ED-based non-coherent massive MIMO systems [7]. Therefore, the proposed adaptive scheme in this paper can be extended to multiple users scenarios. However, for the ease of analysis, we consider SIMO scenario in this study.
Specifically, $d_0$ is $-\infty$ for $\sqrt{p_1}$, $d_K$ is $+\infty$ for $\sqrt{p_K}$ and otherwise
\[
d_k = \left(\frac{p_k + p_{k+1}}{2}\right) \sqrt{p_k \sigma_k^2} + \sigma_k^2, \quad 1 \leq k \leq K - 1.
\]

However, performance loss is expected if the channel condition varies, forcing the system to operate under the worst-case channel conditions. As such, it is essential to effectively adapt to the channel variation.

### B. PROBLEM FORMULATION

Let the candidate non-negative PAM constellations be denoted by set $\mathbf{P} = \{P_0, P_1, \ldots, P_{N-1}\}$, where $N$ is the number of modulation types.\(^2\) In particular, the $j$-th constellation is $P_j = \{\sqrt{p_1}, \sqrt{p_2}, \ldots, \sqrt{p_K}\}$ of size $K_j$. Hence, the spectral efficiency with respect to $P_j$ is $k_j = \log_2 K_j$.

Given the distribution of instantaneous SNR $\gamma$, we partition the possible value of $\gamma$ into $N$ non-overlapping regions $\mathbf{R} = \{R_0, R_1, \ldots, R_{N-1}\}$. The basic concept of adaptive modulation is to map each candidate constellation to $R_j = [\gamma_l^j, \gamma_{l+1}^j)$, where $\gamma_l^j$ denotes the region boundary. That is, if $\gamma$ falls into $R_j$, then $P_{j+1}$ is selected as the modulation scheme. Aiming at finding the optimum $\mathbf{R}^*$, or equivalently the optimum $\gamma^*$, that maximizes the ASE, subject to power and SER constraints, the optimization problem can be formulated as [17]

\[
\mathbf{R}^* = \max_{\mathbf{R}} \sum_{j=0}^{N-1} k_j \int_{\gamma_l^j}^{\gamma_{l+1}^j} f_y(\gamma) \mathrm{d}\gamma
\]

s.t. $C1 : \sum_{j=0}^{N-1} \int_{\gamma_l^j}^{\gamma_{l+1}^j} \frac{P_{tx}(\gamma)}{P_{tx}} f_y(\gamma) \mathrm{d}\gamma = 1$

$C2 : \text{SER}(\gamma) = \text{SER}$.

where $C1$ denotes the power constraint, and $C2$ is the SER requirement with $\text{SER}$ being the target error probability, $f_y(\gamma)$ denotes the distribution of $\gamma$, $P_{tx}(\gamma)$ is the average transmit power and $P_{tx}$ is the transmit power adapted to $\gamma$. The relation between $P_{tx}$ and $P_{tx}(\gamma)$ is
\[
\int_{\gamma_0}^{\infty} P_{tx}(\gamma)f_y(\gamma) \mathrm{d}\gamma = P_{tx}.
\]

where $\gamma_0$ is the cutoff threshold. For wireless communications, an outage event occurs if $\gamma < \gamma_0$. In addition, the power adaptation is given by [19]
\[
\frac{P_{tx}(\gamma)}{P_{tx}} = \frac{S(k_j, \text{SER})}{\gamma}, \quad \gamma_{j-1} \leq \gamma \leq \gamma_j.
\]

where $S(k_j, \text{SER})$ equals the constant received SNR and is a function of modulation type and target SER.

The constrained optimization problem in (5) can be solved by using the Lagrangian method [17]. First, the Lagrange function that maximizes the ASE is formulated as
\[
J(\gamma_0, \gamma_1, \ldots, \gamma_N) = \sum_{j=0}^{N-1} k_j \int_{\gamma_l^j}^{\gamma_{l+1}^j} f_y(\gamma) \mathrm{d}\gamma + \lambda \left(\sum_{j=0}^{N-1} \int_{\gamma_l^j}^{\gamma_{l+1}^j} \frac{S(k_j, \text{SER})f_y(\gamma) \mathrm{d}\gamma}{\gamma} - 1\right),
\]

where $\lambda$ is the Lagrangian multiplier. The optimum boundaries of adaptive modulation are the solutions to equation

\[
\frac{\partial J(\gamma_0, \gamma_1, \ldots, \gamma_N)}{\partial \gamma_j} = 0, \quad 0 \leq j \leq N.
\]

By solving this equation, one can arrive at
\[
\gamma_0^* = \frac{S(k_0, \text{SER})}{k_0}, \quad \gamma_j^* = \frac{S(k_{j+1}, \text{SER}) - S(k_j, \text{SER})}{k_{j+1} - k_j},
\]

where $\rho$ depends on the average power constraint, i.e.,
\[
\sum_{j=0}^{N-1} \int_{\gamma_l^j}^{\gamma_{l+1}^j} \frac{S(k_j, \text{SER})f_y(\gamma) \mathrm{d}\gamma}{\gamma} = 1.
\]

Before further study, we highlight a few points for the adaptive modulation in ED-based non-coherent SIMO systems. Since the optimum $\gamma^*$ relates to $f_y(\gamma)$ and $S(k_j, \text{SER})$, the PDF of instantaneous SNR $\gamma$ is required as priori knowledge. While for $S(k_j, \text{SER})$, we first derive the closed-form

\[
\begin{align*}
\text{FIGURE 1. Decoding regions of a four non-negative PAM constellation over AWGN channel, where } M = 100. \\
\text{Specifically, } d_j \text{ denotes the decision boundary of decoding regions, } d_L = P_{tx}^2 p_k + \sigma_k^2, d_R = P_{tx}^2 p_k - \sigma_k^2.
\end{align*}
\]
expression of SER. Owing to its complex form, the exponential function is employed to approximate the SER expression. Hence, one can obtain \(S(k_j, \overline{SER})\) as a function of the target SER and \(k_j\) since the approximation result is easy to invert. The detailed derivation will be discussed in the next section.

### III. PARAMETRIC ANALYSIS

#### A. SIGNAL-TO-NOISE RATIO

**Lemma 1:** For a chi-square random variable \(\chi^2\) with \(v\) degrees of freedom, one can derive that \(cX \sim \Gamma (k = \frac{v}{2}, \theta = 2c)\) for a positive constant \(c\), where \(\Gamma(\cdot)\) is the Gamma function.

For the sake of analysis, the decision metric of ED-based non-coherent receiver is rewritten as

\[
z = \frac{\mathbf{h}^H \mathbf{P}_x \mathbf{h}}{\mathbf{c}_h^2} \chi^2 + \frac{2n(\mathbf{h}^H \mathbf{h}) \sqrt{\mathbf{P}_x}}{\mathbf{c}_n} x + \frac{n^2 \mathbf{h}^H \mathbf{h}}{\mathbf{c}_n}.
\]

(12)

Since \(M\) is large in the scenario of massive antenna array, the second component \(\omega\) can be approximated to zero. Accordingly, the instantaneous SNR \(\gamma\) is given by

\[
\gamma = \frac{\mathbf{c}_h}{\mathbf{c}_n^2}.
\]

(13)

Since \(\mathbf{P}_x\), \(M\) and \(\mathbf{c}_n^2\) can be regarded as constants, we only need to analyze the distribution of \(\mathbf{h}^H \mathbf{h}\). As elements in \(\mathbf{h}\) follow \(CN(0, \mathbf{c}_h^2)\), \(2\mathbf{h}^H \mathbf{h} / \mathbf{c}_n^2\) is essentially a sum of square of 2\(M\) standard Gaussian random variables, thus we have

\[
2\mathbf{h}^H \mathbf{h} / \mathbf{c}_n^2 \sim \chi^2 (2M).
\]

(14)

where the symbol “\(\sim\)” indicates “follow the distribution of". In addition, the expression in (13) can be transformed into

\[
\gamma = \frac{2\mathbf{h}^H \mathbf{h}}{\mathbf{c}_n^2} \left( \frac{\mathbf{c}_h^2}{\mathbf{c}_n^2} \right)^2 \mathbf{P}_x \mathbf{M}\sigma_n^2.
\]

(15)

By applying Lemma 1, it is obtained that \(\gamma\) follows a Gamma distribution with shape parameter \(M\) and scale factor \(\overline{\gamma}\), where \(\overline{\gamma}\) indicates the average SNR. Consequently, the PDF of \(\gamma\) is

\[
f_{\gamma}(\gamma'; M, \overline{\gamma}) = \frac{1}{\Gamma(M) (\overline{\gamma})^M} \gamma^{M-1} e^{-\frac{\gamma}{\overline{\gamma}}}.
\]

(16)

With (16), the derivation of PDF of \(\gamma\) is complete.

#### B. SER ANALYSIS

In this part, the closed-form expression of SER for a specific \(P_j\) will be derived. For the purpose of briefness, the constellation index \(j\) is omitted. Referring to Fig. 1, the error probability of each constellation point is [7]

\[
P_e(p_k) = \begin{cases} 
1 - F(\gamma; d_k, \sigma^2_k), & k = 1 \\
1 - F(\gamma; d_k, \sigma^2_k) + F(\gamma; d_{k-1}, \sigma^2_k), & 1 < k < K \\
F(\gamma; d_{k}, \sigma^2_k), & k = K
\end{cases}
\]

(17)

where \(F(\gamma; d_k, \sigma^2_k)\) denotes the cumulative distribution function (CDF) of \(\gamma\) subject to \(d_k\) and \(\sigma^2_k\). Let the signal on the \(m\)-th receive antenna be denoted by \(y_m \sim CN(0, \mathbf{P}_x \mathbf{c}_h^2 \mathbf{P}_x + \sigma_n^2)\), then it comes to

\[
Y_m = |y_m|^2 \sim \frac{1}{2} \left( \mathbf{P}_x \mathbf{c}_h^2 \mathbf{P}_x + \sigma_n^2 \right) \chi^2 (2).
\]

(18)

The moment generating function (MGF) of \(Y_m\) is

\[
M_{Y_m}(t) = \frac{1}{1 - (\mathbf{P}_x \mathbf{c}_h^2 \mathbf{P}_x + \sigma_n^2) t}.
\]

(19)

Moreover, the MGF of \(z\) is the product of the MGF of each \(Y_m\), that is

\[
M_z(t) = \prod_{m=1}^{M} M_{Y_m}(t) = \frac{1}{(1 - \psi(p_k)^{t})^M},
\]

(20)

where \(\psi(p_k) = \mathbf{P}_x \mathbf{c}_h^2 \mathbf{P}_x + \sigma_n^2\).

On the other hand, consider a random variable \(\epsilon\) which follows a Gamma distribution, then the MGF of \(\epsilon\) is

\[
M_{\epsilon}(t) = \frac{1}{(1 - \theta t)^\overline{\gamma}}, \quad t < \frac{1}{\overline{\gamma}}.
\]

(21)

According to the property of MGF, the MGF and PDF/CDF of a random variable are uniquely determined. That is, assume \(F_X(x)\) and \(F_Y(y)\), \(M_{\epsilon}(t)\) and \(M_X(t)\) are PDF and MGF of variables \(x\) and \(y\), respectively, then the following relation holds

\[
M_X(t) = M_{\epsilon}(t) \Longleftrightarrow F_X(x) = F_Y(y).
\]

(22)

Via comparing (19) with (21), it can be derived that \(z\) follows a Gamma distribution. In the next, we discuss the derivation of SER and how to approximate it to facilitate our analysis.

1) SER BASED ON THE GAMMA DISTRIBUTION

As the decision metric \(z\) obeys a Gamma distribution, its CDF is

\[
F(z; M, \psi(p_k)) = \frac{1}{\Gamma(M)} \xi(M, \frac{z}{\psi(p_k)}),
\]

(23)

where \(\xi(s, x) = \int_0^s t^{-1} e^{-t} dt\) is the lower incomplete gamma function. Combining (17) and (23), the SER is computed by

\[
P_e^{(\Gamma)} = 1 + \sum_{k=1}^{K} F(d_{k-1}; M, \psi(p_k)) - \sum_{k=1}^{K} F(d_{k}; M, \psi(p_k)).
\]

(24)

where the superscript \((\Gamma)\) indicates that the result is obtained with Gamma distribution. We note that although this result is accurate, its complex form makes (24) difficult to analyze.
2) SER BASED ON THE GAUSSIAN DISTRIBUTION
Since \( z \) is a sum of \( M \) identical but mutually independent \(|y_m|^2\), it can be approximated to a Gaussian random variable according to the central limit theorem, i.e.,

\[
z = \sum_{m=1}^{M} |y_m|^2 \sim \mathcal{N} \left( \mu_z(p_k), \sigma_z^2(p_k) \right),
\]

(25)

where

\[
\mu_z(p_k) = \mathcal{P}_\alpha \sigma_n^2 p_k + \sigma_n^2
\]

\[
\sigma_z^2(p_k) = \frac{1}{M} \left( \mathcal{P}_\alpha \sigma_n^2 p_k + \sigma_n^2 \right)^2.
\]

According to (25), the approximated SER is written as

\[
P_e^{(G)} = \frac{1}{K} \sum_{k=1}^{K} \text{erfc} \left( \frac{\Delta_{L,k}}{\sqrt{2}\sigma_z(p_k)} \right) + \frac{1}{K} \sum_{k=1}^{K} \text{erfc} \left( \frac{\Delta_{R,k}}{\sqrt{2}\sigma_z(p_k)} \right),
\]

(26)

where the superscript \((G)\) indicates that the result is obtained with Gaussian distribution, \(\text{erfc}(\cdot)\) is the complementary error function, \(\Delta_{L,k} = \mathcal{P}_\alpha \sigma_n^2 p_k + \sigma_n^2 - d_{k-1}\) and \(\Delta_{R,k} = d_k - \mathcal{P}_\alpha \sigma_n^2 p_k - \sigma_n^2\), as illustrated in Fig. 1.

C. THE SER APPROXIMATION
It is proved in [7] that the constellation which minimizes the SER assures that each constellation point has equal contribution to the error probability, the result is depicted in (27), as shown at the bottom of the page. Correspondingly, the SER in (26) reduces to

\[
P_e^{(G)} = \text{erfc} \left( \frac{\Delta_{L,1}}{\sqrt{2}\sigma_z(p_1)} \right).
\]

(28)

However, in order to solve the problem in (5), \(\gamma\) is required to be represented as a function of \(P_e^{(G)}\). To this end, we resort to the following lemma.

**Lemma 2:** For a constant \( x > 0 \), the complementary error function can be well approximated as [20]

\[
\text{erfc}(x) \approx \exp \left( -c_1 x - c_2 x^2 \right), \quad x > 0,
\]

(29)

where \(c_1 = 1.095\) and \(c_2 = 0.7565\).

With Lemma 2, the SER in (26) approximates to

\[
P_e^{(G)} \approx \frac{1}{M} \sum_{i=1}^{L} \left\| y_i \right\|_2^2.
\]

(30)

By applying the logarithm operation on both sides of (30), \(\sigma_z(p_1)\) is then represented as a function of \(P_e^{(G)}\):

\[
\sigma_z(p_1) = \frac{-c_1 \Delta_{L,1} - \sqrt{\xi_1 \Delta_{L,1}} - 4c_2 \left( \Delta_{L,1} \right)^2 \ln P_e^{(G)}}{2 \sqrt{2} \ln P_e^{(G)}}.
\]

(31)

In addition, it can be revealed from (25) that

\[
\sigma_z(p_1) = \frac{\sigma_n^2}{\sqrt{M}} \left( p_1 \xi_0 + 1 \right) = \frac{\sigma_n^2}{\sqrt{M}} (p_1 S(k_j, \text{SER}) + 1).
\]

(32)

Then combining (31) and (32), it is readily derived that

\[
S(k_j, \text{SER}) = \frac{\sqrt{M} \sigma_z(p_1)}{p_1 \sigma_n^2} - \frac{1}{p_1}.
\]

(33)

where \(\sigma_z(p_1)\) is shown in (31). Thus, by substituting \(f_\gamma(\gamma)\) and \(S(k_j, \text{SER})\) into (5), it is now ready to solve this problem.

IV. ADAPTIVE MODULATION FOR ED-BASED NON-COHERENT MASSIVE SIMO SYSTEMS
With the former derivation results, we can present the proposed adaptive modulation for ED-based non-coherent massive SIMO systems in a step-by-step manner.

**Step 1:** Estimate the PDF of \(f_\gamma(\gamma; M, \gamma)\). This distribution depends on \(\sigma_n^2\) and \(\sigma_\gamma^2\), which need to be estimated firstly. If user keeps silent, the received signal only contains the noise. Let the signal observed at the \(i\)-th time index be \(y_i = n_i\), the noise variance is estimated by

\[
\hat{\sigma}_n^2 = \frac{1}{MK} \sum_{i=1}^{L} \left\| y_i \right\|_2^2.
\]

(34)

where \(L\) indicates the number of samples used for averaging.

After that, the channel variance is estimated based on (34). Specifically, if the user transmits symbol “1”, the received signal vector is \(y_i = h_i + n_i\). Correspondingly, the estimate of channel variance is

\[
\hat{\sigma}_h^2 = \frac{1}{MK} \sum_{i=1}^{K} \left( y_i^H y_i - \hat{\sigma}_n^2 \right).
\]

(35)
Fig. 2 demonstrates the estimation results of channel and noise variance, where we set $\sigma^2_n = 0.1$ and $\sigma^2_f$. This figure reveals the estimation accuracy critically relies on the parameter $L$, as $\sigma^2_n$ and $\sigma^2_f$ converge to real values along with $L$. Note that the estimation is performed before data transmission and $\sigma^2_n$ and $\sigma^2_f$ are stable over a long period of time. Hence, the delay incurred by a large $L$ is not nontrivial. By inserting (34) and (35) into (16), $f_\gamma(y; M, \overline{\gamma})$ is obtained.

**Step 2:** Calculate the switching thresholds. According to our analysis, given $f_\gamma(y; M, \overline{\gamma})$, average transmit power $P_{tx}$ and target error rate $\overline{SER}$, the switching thresholds can be calculated by solving (5), i.e.,

$$
\gamma_0^* = \frac{S(k_0, \overline{SER})}{k_0} \rho,
$$

$$
\gamma_j^* = \frac{S(k_{j+1}, \overline{SER}) - S(k_j, \overline{SER})}{k_{j+1} - k_j} \rho, \quad 0 < j < N - 1,
$$

(36)

where $\rho$ is computed numerically according to (11).

**Step 3:** Adaptive modulation and channel quality indication (CQI) mapping. Given the optimum region $R_j^* = \{\gamma_j^* \leq \gamma < \gamma_{j+1}^*\}$, CQI can be defined as

$$
CQI = j, \quad \text{if} \quad \gamma_{j-1}^* < \gamma < \gamma_j^*.
$$

(37)

That is, if the instantaneous SNR lies in $R_j^*$, the corresponding CQI is selected. If the number of candidate modulation types is represented by $N = 2^b$, then a binary sequence of length $2^b - 1$ is used to feed back the CQI to the transmitter. Without loss of generality, the feedback relied on a dedicated channel and is supposed to be error free.

**Step 4:** Feedback of CQI and power control. The BS utilizes the information fed back from the user to choose a proper modulation scheme and adjusts the transmit power accordingly. In particular, if the instantaneous SER is higher than $\overline{SER}$, then the optimum regions need to be recalculated, otherwise rate and power adaptation is performed.

It is necessary to study how frequently the recalculation may happen in Step 4 of the proposed algorithm. First, the instantaneous SER correlates strongly to the instantaneous SNR. Then from (15), as $M$ grows large, it can be inferred that $\gamma$ converges to a constant independent of the small-scale fading coefficients. That is, $\gamma$ changes at the same rate of large-scale fading factor. Since large-scale fading factors are relatively stable, the recalculation of the optimum regions doesn’t happen very often in the proposed adaptive scheme.

**V. NUMERICAL RESULTS AND DISCUSSION**

This section will present numerical results of the proposed scheme. Channels of different transmit-receive pairs are modeled by independent Rayleigh fading. Besides, there are four candidate constellations for adaptive modulation, namely 4, 8, 16 and 32 non-negative PAM. Fig. 3 depicts the SER of various non-negative PAM constellations, where “Analytical”, “Approximate” and “Numerical” denote results obtained by (23), (30) and simulations. Clearly, the well match between the numerical results and analytical ones verify our performance analysis. More importantly, the approximate SER of (30) exhibits high accuracy comparing with the other two.

Fig. 4 draws the ASE of non-coherent system with adaptive modulation. We set $\overline{SER} = 10^{-3}$ in Fig. 4 (a). The two fitting between the analytical and numerical results indicates that our analysis can be a good reference for the asymptotic behaviors that is hard to obtain from simulations. It is also worth noting that ASE increases along with $M$. For instance, as $M$ changes from 100 to 400, the average spectral efficiency increases by 1 bps/Hz when SNR = 15 dB. Hence, in scenarios of power restriction, one can maintain the required spectral efficiency by mounting more receive antennas. Alternatively, Fig. 4 (b) considers the relation between ASE and SNR, where $M = 200$ and target error rate varies. We note...
On the other hand, the lower two care about the impact that the OP, the increased cost and complexity must be noticed. While deploying more antennas helps to reduce the gap is about 0.5 bps/Hz. This is expected since lower order need to be applied, which in turn sacrifice the ASE. Evidently, this trade-off between ASE and target SER should be paid special attentions for system design.

VI. CONCLUSION

This paper addresses the adaptive modulation for the ED-based non-coherent massive SIMO systems. By solving the formulated optimization problem, the switching thresholds of SNR that maximize the ASE are obtained. Analytical and numerical results indicate the proposed adaptive modulation effectively enhances the system spectral efficiency. In addition, when applying the adaptive modulation scheme, there exists a trade-off between the target SER and ASE. That is, the ASE reduces when a lower target SER is required. In this situation, mounting more antennas can avoid the loss in ASE, which shows the benefit of massive antenna array.

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