Receive Antenna Selection for MIMO Systems over Correlated Fading Channels

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Abstract—In this letter, we propose a novel receive antenna selection algorithm based on cross entropy optimization to maximize the capacity over spatially correlated channels in multiple-input multiple-output (MIMO) wireless systems. The performance of the proposed algorithm is investigated and compared with the existing schemes. Simulation results show that our low complexity algorithm can achieve near-optimal results that converge to within 99% of the optimal results obtained by exhaustive search. In addition, the proposed algorithm achieves near-optimal results irrespective of the mutual relationship between the number of transmit and receive antennas, the statistical properties of the channel and the operating signal-to-noise ratio.

Index Terms—Channel capacity, correlated channel, cross entropy optimization (CEO), MIMO wireless systems, receive antenna selection.

I. INTRODUCTION

MULTIPLE-INPUT MULTIPLE-OUTPUT (MIMO) wireless systems can dramatically increase the channel capacity through the extra degrees of freedom provided by multiple antenna arrays. In [1], it was demonstrated that the capacity of MIMO systems increases linearly with \( \min(N_T, N_R) \), where \( N_T \) and \( N_R \) denote the number of transmit and receive antennas. However, the higher performance of MIMO systems comes at the expense of increased hardware requirements and computational complexity due to multiple radio frequency (RF) chains required. In order to reduce the hardware cost and preserve the advantages of MIMO systems, a promising technique referred to as antenna selection is presented in [2]. With this method, the RF chains can be optimally connected to the best subset of the transmitter (or receiver) antennas. It has been demonstrated that the system performance using antenna selection techniques is better than the full-complexity systems with the same number of antennas but without selection [2]. However, the superior performance obtained by antenna selection is at the cost of additional computational complexity which grows linearly with \( \binom{M}{L} \), where \( M \) and \( L \) denote the total and selected number of antennas, respectively [3], [4].

Recently, a number of algorithms have been developed for selecting the optimal antenna subset in MIMO wireless systems. For example, in [5], Heath et al. derived a signal-to-noise ratio (SNR) based antenna selection criterion to improve the performance of MIMO systems with linear receivers. In [6], Gore et al. presented antenna selection algorithms to minimize the average probability of error (APE) and to maximize the average throughput. However, an exhaustive search method for antenna selection was used, which is computationally prohibitive for a large array size\(^1\), and is not suitable for implementation in practical systems. To address this problem, some simplified antenna selection algorithms have also been developed, such as norm-based selection (NBS), which can be useful due to its low complexity [2], [7]. Sub-optimal algorithms were presented at a low complexity for receive antenna selection in [4]. Antenna selection approaches based on the theory of optimization were derived in [8]. However, the aforementioned studies have assumed that the MIMO channels are independently fading, which is not strictly true for real propagation environments. For example, in the case of insufficient spacing between antennas or scattering with a small angular spread, the channel capacity will be significantly degraded due to spatial correlation [10]. Thus far, only a small set of published literature investigates antenna selection for correlated channels [11], [12].

In this letter, we formulate the antenna selection problem as a combinatorial optimization problem. Cross entropy optimization (CEO) is used for antenna subset selection at the receiver to maximize the channel capacity\(^2\). The CEO method is so named due to its relation with the Kullback-Leibler distance [13] which is also termed the cross entropy. It is a principled adaptive importance sampling technique devised by Rubinstein [14] to estimate the probabilities of rare events in complex stochastic networks. It was then extended to solve complicated combinatorial optimization problems by considering an optimal event as a rare event, such as non-terministic polynomial time (NP) hard problems [15]. While most stochastic algorithms for combinatorial optimization are based on local search, the CEO method is a global random search procedure whose global convergence has been proven

\(^{1}\)Choosing \( L \) out of \( M \) available antennas leads to a total of \( \binom{M}{L} \) possible combinations for antenna selection at the transmitter or receiver. For example, if \( L = 4 \) and \( M = 16 \), 1820 combinations have to be examined to obtain the optimal antenna selection subset.

\(^{2}\)The proposed CEO method can be also used for the transmit antenna selection with small revisions.
in [15]. The main contribution of this letter is to present a novel receive antenna algorithm based on the CEO method to maximize the capacity over spatially correlated channels. Simulation results indicate that the near-optimal performance of the proposed antenna selection algorithm is not sensitive to the relationship between the number of transmit antennas and the number of selected receive antennas, the statistical properties of channels and the signal-to-noise ratio (SNR), as has been the case with previous approaches.

**Notation:** The following notation is used in this letter. Boldface uppercase and lowercase letters denote matrices and vectors. Plain lowercase letters denote scalars. The superscripts \( (\cdot)^T \) and \((\cdot)^H \) represent the transpose and Hermitian operation. \( E[\cdot] \) denotes the statistical expectation. \( \text{Tr}(\cdot) \) and \( \| \cdot \|_F \) denote the trace and Frobenius norm. \( I_m \) is an \( m \times m \) identity matrix. \( C^{M \times N} \) refers to an \( M \times N \) matrix with complex entries and \( \det(\cdot) \) denotes the determinant operation.

### II. SIGNAL MODEL

Consider a narrowband MIMO wireless system, shown in Figure 1, with \( N_T \) transmit and \( N_R \) receive antennas. The channel is assumed to be flat Rayleigh fading and slow varying with additive white Gaussian noise (AWGN) at the receiver. Then the corresponding received signal is given by [4]

\[
y = Hs + v, \tag{1}
\]

where \( \mathbf{y} \in \mathbb{CN}_R \times 1 \) is the received signal vector, \( \mathbf{s} \in \mathbb{CN}_T \times 1 \) is the transmitted signal vector, \( \mathbf{H} \in \mathbb{CN}_N \times N_T \) is the channel matrix, and \( \mathbf{v} \sim \mathcal{CN}_N \times N_T \) is the additive complex Gaussian noise with zero mean, variance \( \mathcal{N}_0 \) and independently and identically distributed (i.i.d.) entries. \( \mathbf{h}_{ij} \) represents the channel entry between the \( i \)-th transmit and \( j \)-th receive antennas. We assume that perfect channel state information (CSI) is available at the receiver but not at the transmitter, and thus equal power allocation is used at the transmit array. Then, the capacity of the MIMO channel is given by [1]

\[
C = \log_2 \det(\mathbf{I}_{N_T} + \frac{\eta}{N_T} \mathbf{H}^H \mathbf{H}), \tag{4}
\]

where \( \eta \) is the average SNR.

### III. RECEIVE ANTENNA SELECTION

**A. Problem Statement**

Let us denote the number of total and selected receive antennas by \( N_R \) and \( N_r \), respectively \( (N_r \leq N_R) \), the set of all \( \mathcal{A} = \binom{N_R}{N_r} \) antenna subsets as \( \Omega = \{\omega_1, \cdots, \omega_\mathcal{A}\} \) and the indicators of the selected subset of receive antennas by \( I_q = \{I_{i_1} \}_{i_1=1}^{N_R}, \ {I_i} = \{0, 1\}, \) for \( q = 1, 2, \cdots, \mathcal{A} \), \( \tag{5} \)

where \( i \) is the index of the rows of \( \mathbf{H} \) and the indicator function \( I_q \) indicates that the \( i \)-th row of \( \mathbf{H} \) is selected, i.e., the \( i \)-th receive antenna is selected. The receive vector associated with the selection can be written as

\[
y_{\omega_q} = \mathbf{H}_{\omega_q} \mathbf{s}_{\omega_q} + \mathbf{v}_{\omega_q} = [\mathbf{R}_T^{\frac{1}{2}} \omega_q]^H \mathbf{G}_{\omega_q} \mathbf{s}_{\omega_q} + \mathbf{v}_{\omega_q}, \tag{6} \]

where \( \mathbf{y}_{\omega_q} \in \mathbb{CN}_R \times 1, \mathbf{s}_{\omega_q} \in \mathbb{CN}_T \times 1 \) and \( \mathbf{v}_{\omega_q} \in \mathbb{CN}_N \times 1 \) denote the received signal, transmitted signal and noise vectors associated with the selection, respectively. \( \mathbf{H}_{\omega_q} \in \mathbb{CN}_N \times N_T, \mathbf{G}_{\omega_q} \in \mathbb{CN}_N \times N_T \) and \( [\mathbf{R}_T^{\frac{1}{2}} \omega_q]_i \in \mathbb{CN}_N \times N_T \) denote the corresponding channel, the spatially white channel and the receive correlation matrices after the selection, respectively.
B. Selection Criteria

In order to estimate instantaneous channels correctly, the coherence time of channels is assumed to be long enough that the fading coefficients are constant over the entire block and change independently from one block to the next according to the “one ring” spatial correlation model. Therefore, the optimal selected receive antenna index, $\omega^*$, is selected out of $\Omega$ through the training sequence and changes from one block to another [2].

1) Instantaneous CSI (ICSI) Selection Criterion: Assuming that instantaneous CSI is only available at the receiver, the capacity associated with antenna selection is

$$C(\omega_q) = \log_2 \det \left( I_{N_r} + \frac{\eta}{N_T} \mathbf{H}_{\omega_q} \mathbf{H}_{\omega_q}^H \right).$$ (7)

Given the ICSI, we can define the performance function as $S_{ICSI}(\omega_q) = \log_2 \det \left( I_{N_r} + \frac{\eta}{N_T} \mathbf{H}_{\omega_q} \mathbf{H}_{\omega_q}^H \right)$. Therefore, maximizing the capacity associated with the receive antenna selection is equivalent to maximizing

$$\mathcal{P}_1 : \arg \max_{\omega_q \in \Omega} S_{ICSI}(\omega_q).$$ (8)

Since computing the ICSI selection criterion involves singular value decomposition, its complexity is $O(\min\{N_r, N_T\} N_r N_T)$ [16].

2) Norm-based Selection (NBS) Criterion: At low SNR, (7) can be approximated by

$$C(\omega_q) \approx \log_2 \left( 1 + \frac{\eta}{N_T} \text{Tr} \left( \mathbf{H}_{\omega_q} \mathbf{H}_{\omega_q}^H \right) \right)$$ (9)

$$= \log_2 \left( 1 + \frac{\eta}{N_T} \| \mathbf{H}_{\omega_q} \|_F^2 \right).$$

We define the performance function as $S_{NBS}(\omega_q) = \| \mathbf{H}_{\omega_q} \|_F$. Therefore, maximizing the capacity associated with the receive antenna selection is equivalent to maximizing

$$\mathcal{P}_2 : \arg \max_{\omega_q \in \Omega} S_{NBS}(\omega_q),$$ (10)

where $\| \mathbf{H}_{\omega_q} \|_F$ indicates the power of the channel matrix $\mathbf{H}_{\omega_q}$. Although the NBS criterion cannot guarantee an optimal capacity performance, because of its low complexity ($O(N_r N_T)$) [16], it is still a good candidate for antenna selection [2], [5], [7].

3) Spatial Correlation Selection (SCS) Criterion: When the channel is fast fading, channel estimation becomes a difficult task [17]. Moreover, in such a situation, a large number of training sequences have to be used to obtain the optimal receive antenna index, $\omega^*$. These training sequences not only degrade the spectral efficiency but also increase the hardware complexity [18]. Compared with the ICSI, it is easier to estimate and track the spatial correlation because of its slow variation. This makes the SCS criterion desirable for practical MIMO systems with antenna selection. Specifically, at high SNR, (7) can be approximated as

$$C(\omega_q) \approx \log_2 \det \left( \frac{\eta}{N_T} \mathbf{H}_{\omega_q} \mathbf{H}_{\omega_q}^H \right).$$ (11)

Substituting (2) into (11) and using the eigenvalue decomposition (EVD) of $[\mathbf{R}_q]$, we have [11]

$$C(\omega_q) \approx N_T \log_2 \left( \frac{\eta}{N_T} \right) + \log_2 \det \left( \mathbf{G}_{\omega_q} \mathbf{G}_{\omega_q}^H \right)$$

$$+ \log_2 \det \left( [\mathbf{R}_q] \right).$$ (12)

We define the performance function as $S_{SCS}(\omega_q) = \det([\mathbf{R}_q])$. Therefore, when instantaneous CSI is not available, maximizing the capacity is equivalent to maximizing

$$\mathcal{P}_3 : \arg \max_{\omega_q \in \Omega} S_{SCS}(\omega_q).$$ (13)

The computational complexity of the SCS criterion is $O(N_r^2)$.

C. The Cross Entropy Optimization (CEO) Method

The most straightforward approach to obtain the optimal receive antenna subset, $\omega^*$, is by exhaustive search. However, because of its high computational complexity, it becomes prohibitive for MIMO systems with large arrays. In order to reduce the complexity, we formulate the antenna selection problem as a combinatorial optimization problem as follows:

$$\omega^* = \arg \max_{\omega_q \in \Omega} S(\omega_q),$$ (14)

where $\omega^*$ denotes the global optimum of the objective function, $S(\omega_q)$. Here, $S(\omega_q)$ represents the performance functions of $S_{ICSI}(\omega_q)$, $S_{NBS}(\omega_q)$ or $S_{SCS}(\omega_q)$.

After transforming (14) into a combinatorial optimization problem, an iterative algorithm can be used to solve it. The idea of the CEO method is to associate a stochastic estimation problem with the optimization problem (14). Let us define a collection of indicator functions $\{I(S(\omega_q) \geq r)\}$ in the solution space $\Omega$ for various thresholds (or levels) $r \in \{S(\omega_q) : \omega_q \in \Omega\}$, and a number of Bernoulli probability density functions given by

$$f(\omega_q, p) = \prod_{i=1}^{N_r} p_i^I(\omega_q) (1 - p_i)^{1-I(\omega_q)},$$ (15)

where $p_i$ indicates the probability of $i$th receive antenna to be chosen. $I(\omega_q)$ is the indicator for the $i$th element of $\omega_q$. For a given probability distribution $v$, we associate (14) with the following stochastic estimation

$$\ell(r) = \mathbb{E}_v (S(\omega_q) \geq r) = \sum_{\omega_q \in \Omega} I(S(\omega_q) \geq r) f(\omega_q, v)$$

$$= \mathbb{E}_v [I(S(\omega_q) \geq r)],$$ (16)

where $\ell(r)$ is the probability $S(\omega_q) \geq r$ and $I(S(\omega_q) \geq r)$ is given by

$$I(S(\omega_q) \geq r) = \begin{cases} 1, & \text{if } S(\omega_q) \geq r \\ 0, & \text{otherwise} \end{cases}.$$ (17)

A natural way to estimate $\ell$ in (16) is to use a crude Monte Carlo (CMC) simulation by drawing a set of random samples $\{\omega_q^{(n)}\}_{n=1}^N$ from $f(\cdot, v)$, and then the unbiased estimator of $\ell$ is

$$\hat{\ell} = \frac{1}{N} \sum_{n=1}^N I(S(\omega_q^{(n)}) \geq r).$$ (18)
For a large value of \( r \) (i.e. \( r \rightarrow r^* \)), the above problem is a rare event simulation, where \( r^* = \max_{\omega_q \in \Omega} S(\omega_q) \). In order to obtain the optimum, a large number of samples \( N \rightarrow \infty \) have to be drawn to obtain an accurate estimation, because most of the samples are not effective in calculating \( \ell \). Therefore, the CMC method is not suitable for practical applications due to its high complexity.

An alternative way to estimate \( \ell \) is through the importance sampling (IS) technique, drawing a set of random samples \( \{\omega_q^{(n)}\}_{n=1}^N \) from an importance distribution \( g(\omega_q) \). Then the unbiased estimator of \( \ell \) is

\[
\hat{\ell} = \frac{1}{N} \sum_{n=1}^{N} I(\omega_q^{(n)} \geq r) \frac{f(\omega_q^{(n)}, v)}{g(\omega_q^{(n)})}.
\]

(19)

It is well known that the optimal \( g^*(\omega_q) \) is given by [15]

\[
g^* (\omega_q) = \frac{I(\omega_q \geq r) f(\omega_q, v)}{\ell}.
\]

(20)

It is convenient to choose \( g(\omega_q) \) from the parameterized family of densities \( \{f(\cdot, p)\} \). The idea of CEO is to choose the parameter \( p^* \) such that the Kullback-Leibler divergence

\[
\Delta = \int_{\Omega} g^* (\omega_q) \ln \frac{g^* (\omega_q)}{g(\omega_q)} d\omega_q,
\]

is equivalent to solving the following maximization problem [15]

\[
\max_p \int_{\Omega} g^* (\omega_q) \ln f(\omega_q; p) d\omega_q.
\]

(21)

Substituting (20) into (21), we have

\[
\max_p \int_{\Omega} I(\omega_q \geq r) f(\omega_q, v) \ln f(\omega_q; p) d\omega_q,
\]

which is equivalent to

\[
p^* = \arg \max_p \mathbb{E}_v [I(\omega_q^{(n)} \geq r) \ln f(\omega_q^{(n)}; p)].
\]

(23)

Generally it is intractable to obtain a closed-form solution for the optimal parameter \( p^* \), as (23) involves an integration with respect to the density function \( f(\omega_q, v) \). But \( p^* \) can be estimated by the following stochastic program [15]

\[
p^* = \arg \max_p \frac{1}{N} \sum_{n=1}^{N} I(\omega_q^{(n)} \geq r) \ln f(\omega_q^{(n)}; p),
\]

where \( \omega_q^{(n)} \) are the samples drawn from \( f(\omega_q, v) \). Let \( \bar{D}(p) = \frac{1}{N} \sum_{n=1}^{N} I(\omega_q^{(n)} \geq r) \ln f(\omega_q^{(n)}; p) \) and we have

\[
\max_p \bar{D}(p) = \frac{1}{N} \sum_{n=1}^{N} I(\omega_q^{(n)} \geq r) \ln f(\omega_q^{(n)}; p).
\]

(25)

5The Kullback-Leibler divergence between two probability distributions \( g(x) \) and \( f(x) \) is defined as [13]

\[
\Delta(g, f) = \mathbb{E}_q [\ln \frac{g(x)}{f(x)}] = \int g(x) \ln g(x) dx - \int g(x) \ln f(x) dx
\]

4The integration with respect to \( \omega_q \in \Omega \) is a summation when \( \omega_q \) is discrete as in our case. But for generality, it is expressed in the form of integration.

To find the maximum of \( \bar{D}(p) \), we set \( \frac{\partial \bar{D}(p)}{\partial p} = 0 \). Consequently, we have the update rule as follow:

\[
p_i = \frac{\sum_{n=1}^{N} I(\omega_q^{(n)} \geq r) I_i(\omega_q^{(n)})}{\sum_{n=1}^{N} I(\omega_q^{(n)} \geq r)} \quad \text{for } i = 1, 2, \ldots, N_R.
\]

(26)

The update equation (26) is iteratively used with the aim to generate a sequence of increasing thresholds \( p_0^0, p_1^1 \), until convergence to the global optimum \( r^* \) (or to a value close to it) is achieved. At the \( t \)th iteration, a new vector \( p(t) \) is used to draw a set of new samples, which provide better estimates of \( r \). The vector \( p(t) \) is then updated by these samples. This process stops when the stopping criterion is reached. A flowchart of the proposed receive selection algorithm based on the CEO method is described as follows:

**Receive Antenna Selection Algorithm based on the CEO Method**

1. **Step 1:** Start with an initial value \( p(0) = \{p_i(0)\}_{i=1}^{N_R} \). Set the iteration counter \( t := 1 \).
2. **Step 2:** Randomly generate samples \( \{\omega_q^{(n)}\}_{n=1}^{N} \) from the density function \( f(\cdot, p(t-1)) \).
3. **Step 3:** Calculate the performance functions \( \{S(\omega_q^{(n,t)})\}_{n=1}^{N} \) and order them from largest to smallest, \( S(1) \geq \cdots \geq S(N) \). Let \( r(t) \) be the \( (1-\rho)^{th} \) sample quantile of the performances: \( r(t) = S[(1-\rho)N] \), where \( \lceil . \rceil \) is the ceiling operation.
4. **Step 4:** Update the parameter \( p(t) \) via

\[
p_i(t) = \frac{\sum_{n=1}^{N} I(\omega_q^{(n)} \geq r(t)) I_i(\omega_q^{(n)})}{\sum_{n=1}^{N} I(\omega_q^{(n)} \geq r(t))}.
\]

(27)

5. **Step 5:** If the stopping criterion is satisfied, then stop; otherwise set \( t := t + 1 \) and go back to step 2.

Note: In order to prevent occurrences of 0s and 1s in the parameter matrix \( p \), we introduce a smoothing factor \( \lambda \) and change the updating procedure to

\[
p(t) := \lambda * p(t) + (1-\lambda) * p(t-1).
\]

(28)

Clearly, when \( \lambda = 1 \), we have the original updating formulation. The convergence proof of the algorithm is shown in the Appendix.

**IV. SIMULATION RESULTS**

In order to compare and validate the performance of the proposed CEO algorithm, simulations were performed over 10,000 channel realizations using algorithms based on the ICSI, NBS and SCS criteria. For the “one ring” correlated channel model, we assume that a broadside linear array is used at the receiver [10], the antenna spacing (\( d \)) is \( \lambda/2 \) and the directions of arrival (DOA) are uniformly distributed.

These three selection criteria offer a tradeoff between the performance and complexity. The ICSI selection criterion has

5The algorithm converges without the constraint of the starting point, but for simplicity we set \( p_i(0) = \frac{1}{N} \).

6The stopping criterion is \( |r(t) - r(t-1)| \leq \beta \) where \( \beta \) is the stopping threshold and set as \( 10^{-2} \) in this letter.
the best performance but has the highest hardware and computational complexity, while the NBS criterion has the lowest complexity but this is achieved at the cost of performance. The SCS criterion is a possible compromise, but its performance is inferior for both the ICSI selection and SCS criteria. Compared with the CEO algorithm and LCS method, the capacity performance obtained by the GC method is nearly the same as that by exhaustive search (ES) for a wide range of SNR. The NBS algorithm is not suitable for antenna selection. Fig. 3 also shows receive antenna selection by a low complexity selection (LCS) method [11] and Gerschgorin circles (GC) method [12] for comparison. From the figure, it can be seen that the LCS method obtains near-optimal capacity performance for the ICSI selection criterion but suffers a performance loss for the SCS criterion. Compared with the CEO algorithm and LCS method, the capacity performance obtained by the GC method is inferior for both the ICSI selection and SCS criteria.

The 10% outage capacity versus \( N_r \) with \( N_R = 16 \) and \( N_T = 20 \) dB at \( \Delta = 120^\circ \) and \( \Delta = 30^\circ \) is shown in Fig. 4. It can be seen that the CEO algorithm can obtain near-optimal performance for both the ICSI and SCS and this performance is independent of the selected receive antenna array size (\( N_r \)). The LCS method can also obtain near-optimal performance for the ICSI but not for the SCS, especially when \( N_r \geq 6 \). Compared with the LCS method, the GC method exhibits superior performance for the SCS when \( N_r \leq 6 \) and becomes inferior when \( N_r \geq 8 \). The results in Fig. 5 illustrate the

Fig. 2. Performance comparison between three selection criteria by exhaustive search.

(a) 10% outage capacity versus SNR with \( N_R = 16 \) and \( N_T = 4 \) for various angle spreads (\( \Delta \)).

(b) 10% outage capacity versus \( N_r \) with \( N_R = 16 \), \( N_T = 4 \) and SNR = 20 dB for various angle spreads (\( \Delta \)).

As a result, the simulation results from Fig. 2 show that the outage capacity performance of SCS is close to that of ICSI at large \( N_r \) or small angle spread. In this letter, we assume that SCS can replace ICSI for receive antenna selection at \( N_r \geq 6 \) or \( \Delta \leq 60^\circ \) when \( N_R = 16 \) and \( N_T = 4 \).

Fig. 3 shows the 10% outage capacity versus SNR with \( N_R = 16 \) and \( N_r = N_T = 4 \) at \( \Delta = 120^\circ \) and \( \Delta = 60^\circ \). Based on the analysis in Fig. 2, SCS can replace ICSI to obtain near-optimal results at a small angle spread. Thus, SCS is used when \( \Delta = 60^\circ \) while ICSI is used when \( \Delta = 120^\circ \). The results indicate that the outage capacity achieved by the CEO algorithm is nearly the same as that by exhaustive search (ES) for a wide range of SNR. The NBS algorithm has near-optimal performance in the low SNR region (SNR \( \leq 5 \) dB). However, when the value of SNR increases, the performance of the NBS algorithm is no longer optimal and even worse than the random selection algorithm (RSA) when SNR \( \geq 10 \) dB. Hence, in the high SNR regime with spatial correlation, the NBS algorithm is not suitable for antenna selection. Fig. 3 also shows receive antenna selection by a low complexity selection (LCS) method [11] and Gerschgorin circles (GC) method [12] for comparison. From the figure, it can be seen that the LCS method obtains near-optimal capacity performance for the ICSI selection criterion but suffers a performance loss for the SCS criterion. Compared with the CEO algorithm and LCS method, the capacity performance obtained by the GC method is inferior for both the ICSI selection and SCS criteria.
TABLE I

Complexity Comparisons for Various Antenna Selection Algorithms with \( N_R = 16, N_T = 4, \eta = 20 \) dB

| \((N_R, N_T)\) | Number of samples (\( N \)) | Number of iterations (\( t \)) | CEO | LCS [11] | GC [12] | ES |
|----------------|-----------------------------|-------------------------------|-----|----------|---------|----|
| (16, 2)        | 15                          | 5                             | 75  | 135      | 15     | 120|
| (16, 4)        | 18                          | 5                             | 90  | 126      | 78     | 1820|
| (16, 6)        | 20                          | 5                             | 100 | 115      | 165    | 1820|
| (16, 8)        | 20                          | 5                             | 100 | 100      | 252    | 12870|
| (16, 10)       | 20                          | 5                             | 100 | 81       | 315    | 8008|
| (16, 12)       | 18                          | 5                             | 90  | 58       | 330    | 1820|
| (16, 14)       | 15                          | 5                             | 75  | 31       | 273    | 120|

outage capacity versus the angle spread (\( \Delta \)) with \( N_R = 16, N_T = 4, \eta = 20 \) dB at \( \Delta = 120^\circ \) based on the instantaneous CSI selection criterion (Solid Line) and \( \Delta = 30^\circ \) based on the spatial correlation selection criterion (Dashed Line).

Fig. 4. 10\% outage capacity versus \( N_r \) with \( N_R = 16 \) and SNR = 20 dB at \( \Delta = 120^\circ \) based on the instantaneous CSI selection criterion (Solid Line) and \( \Delta = 30^\circ \) based on the spatial correlation selection criterion (Dashed Line).

Fig. 5. 10\% outage capacity versus the angle spread (\( \Delta \)) with \( N_R = 16, N_T = 4, \eta = 20 \) dB at \( \Delta = 120^\circ \) based on the instantaneous CSI selection criterion (Solid Line) and \( \Delta = 30^\circ \) based on the spatial correlation selection criterion (Dashed Line).

V. Conclusion

In this letter, we have presented a novel receive antenna selection algorithm based on cross entropy optimization (CEO) to maximize the channel capacity over spatially correlated channels. Simulations demonstrate that the proposed algorithm can obtain near-optimal results with rapid convergence. In addition, we find that the proposed algorithm performs well irrespective of the SNR, the angle spread, the selected receive antenna array size and the mutual relationship between the transmit and selected receive antenna array size.

APPENDIX

Convergence Proof of the Proposed Receive Antenna Selection Algorithm

To begin, we define the Bernoulli p.d.f. for the \( t \)th iteration of the \( i \)th antenna (in \( \omega \)) as

\[
f_{i,t}(\omega, p) \triangleq p_{i,t}^{\omega_i,t}(1 - p_{i,t})^{1 - \omega_i,t},
\]

where \( \omega_i,t \) denotes the \( i \)th element of \( \omega \) at the \( t \)th iteration. Assume the following condition is satisfied

\[
\lambda_t \geq \frac{t}{t + 1}
\]

for some \( T \geq 0 \). Without loss of generality, let \( T \geq 1 \). Then, according to (28) and \( t \geq T \), we have

\[
p_{i,t} \geq \prod_{m=0}^{t-1} \lambda_m \cdot p_{i,0} \geq \prod_{m=0}^{T-1} \lambda_m \cdot \prod_{m=T}^{m+1} \frac{m}{m+1} \cdot p_{i,0}
\]

where \( \kappa \) is a constant and equal to \( \prod_{m=0}^{T-1} \lambda_m \cdot T \). Since \( \kappa \geq 0 \), we have \( p_{i,t} \geq \frac{p_{i,0}}{t} \), which further implies, with probability one, that

\[
f_{i,t}(\omega, p) \geq f_{i,0}(\omega, p) \frac{p_{i,0}}{t}, \quad \text{for } t = 1, 2, 3, \ldots
\]
The probability of lack of convergence to the optimal point $\omega^*$ is therefore bounded by

$$\Pr(\omega(t) \neq \omega^*) = \prod_{t=1}^{\infty} \prod_{i=1}^{N_t} (1 - f_{i,t}(\omega^*, p))$$

$$\leq \prod_{t=1}^{\infty} \prod_{i=1}^{N_t} \left(1 - \frac{f_{i,0}(\omega^*, p)}{t}\right)$$

$$\leq \prod_{t=1}^{\infty} \prod_{i=1}^{N_t} e^{-\frac{f_{i,0}(\omega^*, p)}{t}}$$

$$= e^{-\sum_{i=1}^{N_t} f_{i,0}(\omega^*, p) \sum_{t=1}^{\infty} \frac{1}{t}}.$$  

When $t \to \infty$, we can obtain

$$\sum_{t=1}^{\infty} \frac{1}{t} \to \infty.$$  

Therefore, we finally have

$$0 \leq \lim_{t \to \infty} \Pr(\omega(t) \neq \omega^*)$$

$$\leq \lim_{t \to \infty} e^{-\sum_{i=1}^{N_t} f_{i,0}(\omega^*, p) \sum_{t=1}^{\infty} \frac{1}{t}} = 0,$$

which implies that $\lim_{t \to \infty} \Pr(\omega(t) = \omega^*) = 1$. This completes the proof.

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