Detection in Large-Scale Multiuser SM-MIMO Systems: Algorithms and Performance

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***Abstract*—In this paper, we propose algorithms for signal detection in large-scale multiuser *spatial modulation multiple-input multiple-output (SM-MIMO)* systems. In large-scale SM-MIMO, each user is equipped with multiple transmit antennas (e.g., 2 or 4 antennas) but only one transmit RF chain, and the base station (BS) is equipped with tens to hundreds of (e.g., 128) receive antennas. In SM-MIMO, in a given channel use, each user activates any one of its multiple transmit antennas and the index of the activated antenna conveys information bits in addition to the information bits conveyed through conventional modulation symbols (e.g., QAM). We propose two different algorithms for detection of large-scale SM-MIMO signals at the BS; one is based on *message passing* and the other is based on *local search*. The proposed algorithms are shown to achieve very good performance and scale well. Also, for the same spectral efficiency, multiuser SM-MIMO outperforms conventional multiuser MIMO (recently being referred to as massive MIMO) by several dBs; for e.g., with 16 users, 128 antennas at the BS and 4 bpcu per user, SM-MIMO with 4 transmit antennas per user and 4-QAM outperforms massive MIMO with 1 transmit antenna per user and 16-QAM by about 4 to 5 dB at 10^{-3} uncoded BER. This SNR advantage essentially comes about because the spatial index bits allow SM-MIMO to achieve a given spectral efficiency using a lower order modulation alphabet than in conventional multiuser MIMO.**

I. INTRODUCTION

Large-scale MIMO systems with tens to hundreds of antennas are getting increased research attention [1]-[5]. The following two characteristics are typical in conventional MIMO systems: (i) there will be one transmit RF chain for each transmit antenna (i.e., if n_t is the number of transmit antennas, the number of transmit RF chains will also be n_t), and (ii) information bits are carried only on the modulation symbols (e.g., QAM). Spatial modulation MIMO (SM-MIMO) systems [6] differ from conventional MIMO systems in the following two aspects: (i) in SM-MIMO there will be multiple transmit antennas but only one transmit RF chain, and (ii) the index of the active transmit antenna will also convey information bits in addition to information bits conveyed through modulation symbols like QAM. The advantages of SM-MIMO include reduced RF hardware and complexity, size, and cost.

Several works have focused on single user point-to-point SM-MIMO systems ([7] and the references therein). Some works on multiuser SM-MIMO have also been reported [8]-[10]. An interesting result reported in [8] is that multiuser SM-MIMO outperforms conventional multiuser MIMO by several dBs for the same spectral efficiency. This work is limited to 3 users (with 4 antennas each) and 4 antennas at BS receiver. Also, only maximum likelihood (ML) detection is considered. This superiority of SM-MIMO over conventional MIMO attracts further investigations on multiuser SM-MIMO. In particular, investigations in the following two directions are of interest: (i) large-scale SM-MIMO (with large number of users and BS antennas), and (ii) detection algorithms that can scale and perform well in such large-scale SM-MIMO systems. In this paper, we make contributions in these two directions.

Recently, conventional multiuser MIMO systems with large number of antennas at the BS are referred to as 'massive MIMO' systems [5]. We investigate multiuser SM-MIMO with similar number of users and BS antennas envisaged in massive MIMO, e.g., tens of users and hundreds of BS antennas. Our contributions can be summarized as follows.

- Proposal of two different algorithms for detection of large-scale SM-MIMO signals at BS. One algorithm is based on *message passing* referred to as MPD-SM (message passing detection for spatial modulation) algorithm, and the other is based on *local search* referred to as LSD-SM (local search detection for spatial modulation) algorithm. Simulation results show that these algorithms achieve very good performance and scale well.
- Comparison between SM-MIMO and massive MIMO for the same spectral efficiency. Simulation results show that SM-MIMO outperforms massive MIMO by several dBs; e.g., SM-MIMO has a 4 to 5 dB SNR advantage over massive MIMO at 10^{-3} BER for 16 users, 128 BS antennas, and 4 bpcu per user. The SNR advantage of SM-MIMO over massive MIMO is attributed to the fact that, because of the spatial index bits, SM-MIMO can use a smaller sized QAM alphabet to achieve the same spectral efficiency as in massive MIMO.

II. SYSTEM MODEL

Consider a multiuser system with K uplink users communicating with a BS having N receive antennas, where N is in the order of tens to hundreds. The ratio $\alpha = K/N$ is the system loading factor. Each user employs spatial modulation (SM) for transmission, where each user has n_t transmit antennas but only one transmit RF chain (see Fig. 1). In a given channel use, each user selects any one of its n_t transmit antennas, and transmits a symbol from a modulation alphabet $\mathbb{A}$ on the selected antenna. The number of bits conveyed per channel use per user through the modulation symbols is $\lfloor \log_2 |\mathbb{A}| \rfloor$. In addition, $\lfloor \log_2 n_t \rfloor$ bits per channel use (bpcu) per user is conveyed through the index of the chosen transmit antenna. Therefore, the overall system throughput is $K(\lfloor \log_2 |\mathbb{A}| \rfloor + \lfloor \log_2 n_t \rfloor)$ bpcu. For example, in a system with $K = 3$, $n_t = 4$, 4-QAM, the system throughput is 12 bpcu. Fig. 1 shows the multiuser SM-MIMO system model.

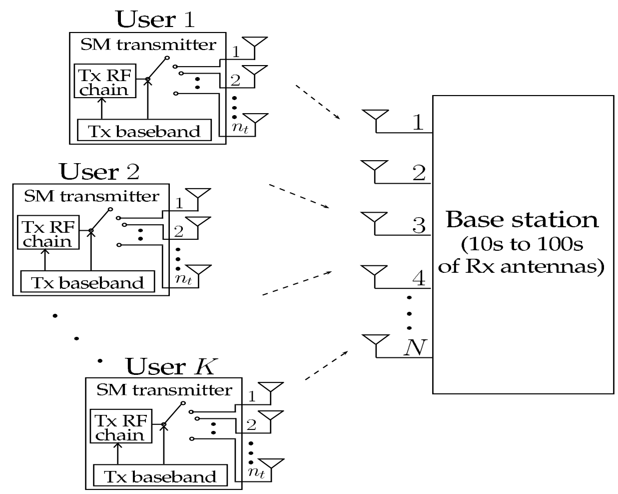
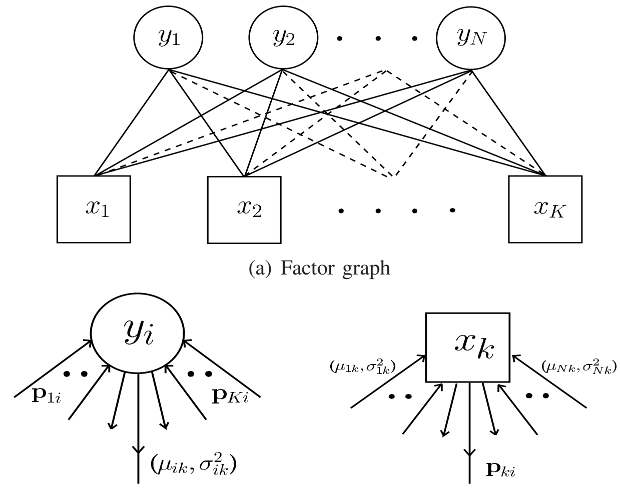


Fig. 1. Large-scale multiuser SM-MIMO system.



(a) Factor graph

(b) Observation node messages (c) Variable node messages

Fig. 2. The factor graph and messages passed in MPD-SM algorithm.

The SM signal set $\mathbb{S}_{n_t,\mathbb{A}}$ for each user is given by

$$\mathbb{S}_{n_t,\mathbb{A}} = \big\{\mathbf{s}_{j,l} : j = 1, \cdots, n_t, \quad l = 1, \cdots, |\mathbb{A}|\big\},$$
$$\text{s.t.} \quad \mathbf{s}_{j,l} = [0, \cdots, 0, \underbrace{s_l}_{j\text{th coordinate}}, 0, \cdots, 0]^T, \quad s_l \in \mathbb{A}. \tag{1}$$

For example, for $n_t = 2$ and 4-QAM, $\mathbb{S}_{n_t,\mathbb{A}}$ is given by

$$\mathbb{S}_{2,\text{4-QAM}} = \left\{ \begin{bmatrix} +1+j \\ 0 \end{bmatrix}, \begin{bmatrix} +1-j \\ 0 \end{bmatrix}, \begin{bmatrix} -1+j \\ 0 \end{bmatrix}, \begin{bmatrix} -1-j \\ 0 \end{bmatrix}, \right.$$
$$\left. \begin{bmatrix} 0 \\ +1+j \end{bmatrix}, \begin{bmatrix} 0 \\ +1-j \end{bmatrix}, \begin{bmatrix} 0 \\ -1+j \end{bmatrix}, \begin{bmatrix} 0 \\ -1-j \end{bmatrix} \right\}. \tag{2}$$

Let $\mathbf{x}_k \in \mathbb{S}_{n_t,\mathbb{A}}$ denote the transmit vector from user k. Let $\mathbf{x} \triangleq [\mathbf{x}_1^T \ \ \mathbf{x}_2^T \ \cdots \ \mathbf{x}_k^T \ \cdots \ \mathbf{x}_K^T]^T$ denote the vector comprising of transmit vectors from all the users. Note that $\mathbf{x} \in \mathbb{S}_{n_t,\mathbb{A}}^K$.

Let $\mathbf{H} \in \mathbb{C}^{N \times Kn_t}$ denote the channel gain matrix, where $H_{i,(k-1)n_t+j}$ denotes the complex channel gain from the jth transmit antenna of the kth user to the ith BS receive antenna. The channel gains are assumed to be independent Gaussian with zero mean and variance σ_k^2, such that $\sum_k \sigma_k^2 = K$. The σ_k^2 models the imbalance in the received power from user k due to path loss etc., and $\sigma_k^2 = 1$ corresponds to the case of perfect power control. Assuming perfect synchronization, the received signal at the ith BS antenna is given by

$$y_i = \sum_{k=1}^{K} x_{l_k} H_{i,(k-1)n_t+j_k} + n_i, \tag{3}$$

where x_{l_k} is the l_kth symbol in $\mathbb{A}$, transmitted by the j_kth antenna of the kth user, and n_i is the noise modeled as a complex Gaussian random variable with zero mean and variance σ^2. The received signal at the BS antennas can be written in vector form as

$$\mathbf{y} \ = \ \mathbf{H}\mathbf{x} + \mathbf{n}, \tag{4}$$

where $\mathbf{y} = [y_1, \ y_2, \cdots, \ y_N]^T$ and $\mathbf{n} = [n_1, \ n_2, \cdots, \ n_N]^T$.

For this system model, the maximum-likelihood (ML) detection rule is given by

$$\hat{\mathbf{x}} = \underset{\mathbf{x} \in \mathbb{S}_{n_t,\mathbb{A}}^K}{\text{argmin}} \ \|\mathbf{y} - \mathbf{H}\mathbf{x}\|^2, \tag{5}$$

where $\|\mathbf{y} - \mathbf{H}\mathbf{x}\|^2$ is the ML cost. The maximum a posteriori probability (MAP) decision rule, is given by

$$\hat{\mathbf{x}} = \underset{\mathbf{x} \in \mathbb{S}_{n_t,\mathbb{A}}^K}{\text{argmax}} \ \Pr(\mathbf{x} \mid \mathbf{y}, \mathbf{H}). \tag{6}$$

Since $|\mathbb{S}_{n_t,\mathbb{A}}^K| = (|\mathbb{A}|n_t)^K$, the exact computation of (5) and (6) requires exponential complexity in K. We propose two low complexity detection algorithms for multiuser SM-MIMO; one based on message passing (Sec. III) which gives an approximate solution to (6), and another based on local search (Sec. IV) which gives an approximate solution to (5).

Note that in conventional multiuser MIMO, the vector $\mathbf{x}$ in (4) is $\mathbf{x} \in \mathbb{B}^K$ where $\mathbb{B}$ is the modulation alphabet, and $\mathbf{H} \in \mathbb{C}^{N \times K}$. The condition for SM-MIMO and conventional MIMO to have the same system throughput is $|\mathbb{B}| = |\mathbb{A}|n_t$.

III. Message Passing Detection for SM-MIMO

In this section, we propose a message passing based algorithm for detection in SM-MIMO systems. We refer to the proposed algorithm as the MPD-SM (message passing detection for spatial modulation) algorithm. We model the system as a fully connected factor graph with K variable (or factor) nodes corresponding to $\mathbf{x}_k$'s and N observation nodes corresponding to y_i's, as shown in Fig. 2(a).

Messages: We derive the messages passed in the factor graph as follows. Equation (4) can be written as

$$y_i = \mathbf{h}_{i,[k]}\mathbf{x}_k + \underbrace{\sum_{j=1, j \neq k}^{K} \mathbf{h}_{i,[j]}\mathbf{x}_j + n_i}_{\triangleq \ g_{ik}}, \tag{7}$$

where $\mathbf{h}_{i,[j]}$ is a row vector of length n_t, given by $[H_{i,(j-1)n_t+1} \quad H_{i,(j-1)n_t+2} \cdots H_{i,jn_t}]$, and $\mathbf{x}_j \in \mathbb{S}_{n_t,\mathbb{A}}$.

We approximate the term g_{ik} to have a Gaussian distribution[1] with mean μ_{ik} and variance σ_{ik}^2 as follows.

[1]This Gaussian approximation will be accurate for large K; e.g., in systems with tens of users.

$$\mu_{ik} = \mathbb{E}\Big[\sum_{j=1,j\neq k}^{K} \mathbf{h}_{i,[j]}\mathbf{x}_j + n_i\Big] = \sum_{j=1,j\neq k}^{K} \sum_{\mathbf{s}\in\mathbb{S}_{n_t,\mathbb{A}}} p_{ji}(\mathbf{s})\mathbf{h}_{i,[j]}\mathbf{s}$$
$$= \sum_{j=1,j\neq k}^{K} \sum_{\mathbf{s}\in\mathbb{S}_{n_t,\mathbb{A}}} p_{ji}(\mathbf{s}) s_{l_s} H_{i,(j-1)n_t+l_s}, \quad (8)$$

where s_{l_s} is the only non-zero entry in $\mathbf{s}$ and l_s is its index, and $p_{ki}(\mathbf{s})$ is the message from kth variable node to the ith observation node. The variance is given by

$$\sigma_{ik}^2 = \text{Var}\Big(\sum_{j=1,j\neq k}^{K} \mathbf{h}_{i,[j]}\mathbf{x}_j + n_i\Big)$$
$$= \sum_{j=1,j\neq k}^{K} \sum_{\mathbf{s}\in\mathbb{S}_{n_t,\mathbb{A}}} p_{ji}(\mathbf{s})\big|s_{l_s}H_{i,(j-1)n_t+l_s}\big|^2 - \Big|\sum_{\mathbf{s}\in\mathbb{S}_{n_t,\mathbb{A}}} p_{ji}(\mathbf{s}) s_{l_s} H_{i,(j-1)n_t+l_s}\Big|^2 + \sigma^2. \quad (9)$$

The message $p_{ki}(\mathbf{s})$ is given by

$$p_{ki}(\mathbf{s}) \propto \prod_{m=1,m\neq i}^{N} \exp\Big(-\frac{\big|y_m - \mu_{mk} - \mathbf{h}_{m,[k]}\mathbf{s}\big|^2}{2\sigma_{mk}^2}\Big). \quad (10)$$

Message passing: The message passing is done as follows.

Step 1: Initialize $p_{ki}(\mathbf{s})$ to $1/|\mathbb{S}_{n_t,\mathbb{A}}|$ for all i, k and $\mathbf{s}$.
Step 2: Compute μ_{ik} and σ_{ik}^2 from (8) and (9), respectively.
Step 3: Compute p_{ki} from (10). To improve the convergence rate, damping [11] of the messages in (10) is done with a damping factor $\delta \in (0, 1]$.

Repeat Steps 2 and 3 for a certain number of iterations. Figures 2(b) and 2(c) illustrate the exchange of messages between observation and variable nodes, where the vector message $\mathbf{p}_{ki} = [p_{ki}(\mathbf{s}_1), p_{ki}(\mathbf{s}_2), \cdots, p_{ki}(\mathbf{s}_{|\mathbb{S}_{n_t,\mathbb{A}}|})]$. The final symbol probabilities at the end are given by

$$p_k(\mathbf{s}) \propto \prod_{m=1}^{N} \exp\Big(-\frac{\big|y_m - \mu_{mk} - \mathbf{h}_{m,[k]}\mathbf{s}\big|^2}{2\sigma_{mk}^2}\Big). \quad (11)$$

The detected vector of the kth user at the BS is obtained as

$$\hat{\mathbf{x}}_k = \underset{\mathbf{s}\in\mathbb{S}_{n_t,\mathbb{A}}}{\text{argmax}}\ p_k(\mathbf{s}). \quad (12)$$

The non-zero entry in $\hat{\mathbf{x}}_k$ and its index are then demapped to obtain the information bits of the kth user. The algorithm listing is given in **Algorithm 1**.

Complexity: From (8), (9), and (10), we see that the total complexity of the MPD-SM algorithm is $O(NK|\mathbb{S}_{n_t,\mathbb{A}}|)$. This complexity is less than the MMSE detection complexity of $O(N^2Kn_t)$. Also, the computation of double summation in (8) and (9) can further be simplified by using FFT, as the double summation can be viewed as a convolution operation.

Performance: We evaluated the performance of multiuser SM-MIMO using the proposed MPD-SM algorithm and compared it with that of massive MIMO with ML detection (using sphere decoder) for the same spectral efficiency with $K = 16$ and $N = 64, 128$. It is noted that in both SM-MIMO and massive MIMO systems, the number of transmit RF chains at each user is $n_{rf} = 1$. For SM-MIMO, we consider the

Input: $\mathbf{y}$, $\mathbf{H}$, σ^2
Initialize: $p_{ki}^{(0)}(\mathbf{s}) \leftarrow 1/|\mathbb{S}_{n_t,\mathbb{A}}|, \forall i,k,\mathbf{s}$
for $t = 1 \rightarrow Number\_of\_iterations$ **do**
  for $i = 1 \rightarrow N$ **do**
    for $j = 1 \rightarrow K$ **do**
      $\tilde{\mu}_{ij} \leftarrow \sum_{\mathbf{s}\in\mathbb{S}_{n_t,\mathbb{A}}} p_{ji}^{(t-1)}(\mathbf{s}) s_{l_s} H_{i,(j-1)n_t+l_s}$
    end
    $\mu_i \leftarrow \sum_{j=1}^{K} \tilde{\mu}_{ij}$
    $\sigma_i^2 \leftarrow \sum_{j=1}^{K} \sum_{\mathbf{s}\in\mathbb{S}_{n_t,\mathbb{A}}} p_{ji}^{(t-1)}(\mathbf{s})\big|s_{l_s}H_{i,(j-1)n_t+l_s}\big|^2 - \big|\tilde{\mu}_{ij}\big|^2 + \sigma^2$
    for $k = 1 \rightarrow K$ **do**
      $\mu_{ik} \leftarrow \mu_i - \tilde{\mu}_{ik}$
      $\sigma_{ik}^2 \leftarrow \sigma_i^2 - \sum_{\mathbf{s}\in\mathbb{S}_{n_t,\mathbb{A}}} p_{ki}^{(t-1)}(\mathbf{s})\big|s_{l_s}H_{i,(k-1)n_t+l_s}\big|^2 + \big|\tilde{\mu}_{ik}\big|^2$
    end
  end
  for $k = 1 \rightarrow K$ **do**
    foreach $\mathbf{s} \in \mathbb{S}_{n_t,\mathbb{A}}$ **do**
      $\ln(p_k(\mathbf{s})) \leftarrow C_k - \sum_{m=1}^{N} \frac{\big|y_m - \mu_{mk} - \mathbf{h}_{m,[k]}\mathbf{s}\big|^2}{2\sigma_{mk}^2}$
      C_k is a normalizing constant.
    end
    for $i = 1 \rightarrow N$ **do**
      foreach $\mathbf{s} \in \mathbb{S}_{n_t,\mathbb{A}}$ **do**
        $\tilde{p}_{ki}(\mathbf{s}) \leftarrow \ln(p_k(\mathbf{s})) + \ln(\sigma_{ik}) + \frac{\big|y_i - \mu_{ik} - \mathbf{h}_{i,[k]}\mathbf{s}\big|^2}{2\sigma_{ik}^2}$
        $p_{ki}^{(t)}(\mathbf{s}) = (1-\delta)\exp(\tilde{p}_{ki}^{(t)}(\mathbf{s})) + \delta p_{ki}^{(t-1)}(\mathbf{s})$
      end
    end
  end
end
Output: $p_k(\mathbf{s})$ as per (11) and $\hat{\mathbf{x}}_k$ as per (12), $\forall k$

Algorithm 1: Listing of the proposed MPD-SM algorithm.

number of transmit antennas at each user to be $n_t = 2, 4$. Figure 3 shows the performance comparison between SM-MIMO with ($n_t = 2$, 4-QAM) and massive MIMO with ($n_t = 1$, 8-QAM), both having 3 bpcu per user. From Fig. 3, we can see that SM-MIMO outperforms massive MIMO by several dBs. For example, at a BER of 10^{-3}, SM-MIMO has a 2.5 to 3.5 dB SNR advantage over massive MIMO. We have observed (see Fig. 4) about 3 to 4 dB SNR advantage for SM-MIMO with ($n_t = 4$, 4-QAM) compared to massive MIMO with ($n_t = 1$, 16-QAM), both at 4 bpcu per user. This SNR advantage in favor of SM-MIMO can be explained as follows. Since SM-MIMO conveys information through antenna indices in addition to carrying bits on QAM symbols, SM-MIMO can use a smaller-sized QAM compared to that used in massive MIMO to achieve the same spectral efficiency, and a small-sized QAM is more power efficient than a larger one.

IV. LOCAL SEARCH DETECTION FOR SM-MIMO

In this section, we propose another algorithm for SM-MIMO detection. The algorithm is based on local search. The algorithm finds a local optimum (in terms of ML cost) as the solution through a local neighborhood search. We refer to this algorithm as LSD-SM (local search detection for spatial modulation) algorithm. A key to the LSD-SM algorithm is the definition of a neighborhood suited for SM. This is important since SM carries information bits in the antenna indices also.

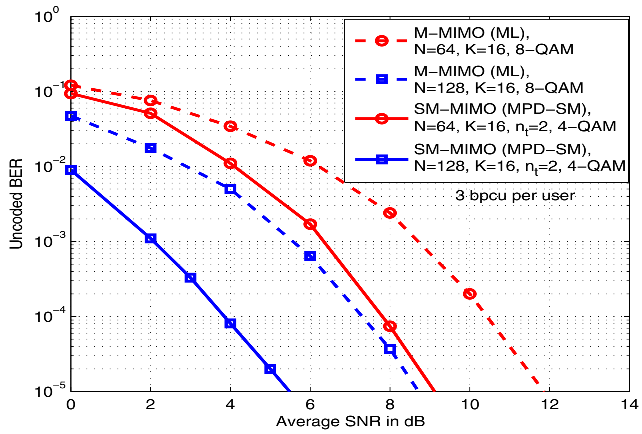


Fig. 3. BER performance of multiuser SM-MIMO ($n_t = 2$, $n_{rf} = 1$, 4-QAM) using MPD-SM algorithm and massive MIMO ($n_t = 1$, $n_{rf} = 1$, 8-QAM) with sphere decoding, at 3 bpcu per user, $K = 16$, $N = 64, 128$.

Neighborhood definition: For a given vector $\mathbf{x} \in \mathbb{S}^K_{n_t,\mathbb{A}}$, we define the neighborhood $\mathcal{N}(\mathbf{x})$ to be the set of all vectors in $\mathbb{S}^K_{n_t,\mathbb{A}}$ that differ from the vector $\mathbf{x}$ in either one spatial index position or in one modulation symbol. That is, a vector $\mathbf{w}$ is said to be a neighbor of $\mathbf{x}$ if and only if $\mathbf{w}_k \in \{\mathbb{S}_{n_t,\mathbb{A}} \setminus \mathbf{x}_k\}$ for exactly one k, and $\mathbf{w}_k = \mathbf{x}_k$ for all other k, i.e., the neighborhood $\mathcal{N}(\mathbf{x})$ is given by

$$\mathcal{N}(\mathbf{x}) \triangleq \left\{\mathbf{w} | \mathbf{w} \in \mathbb{S}^K_{n_t,\mathbb{A}}, \mathbf{w}_k \neq \mathbf{x}_k \text{ for exactly one } k\right\}, \quad (13)$$

where $\mathbf{x}_k, \mathbf{w}_k \in \mathbb{S}_{n_t,\mathbb{A}}$ and $k \in 1, 2, \cdots, K$. Thus the size of this neighborhood is given by $|\mathcal{N}(\mathbf{x})| = (|\mathbb{S}_{n_t,\mathbb{A}}| - 1)K$.

For example, consider $K = 2$, $n_t = 2$, and BPSK (i.e., $\mathbb{A} = \{\pm 1\}$). We then have $\mathbb{S}_{2,\text{BPSK}} = \left\{ \begin{bmatrix} +1 \\ 0 \end{bmatrix}, \begin{bmatrix} -1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ +1 \end{bmatrix}, \begin{bmatrix} 0 \\ -1 \end{bmatrix} \right\}$, and

$$\mathcal{N}\left(\begin{bmatrix} +1 \\ 0 \\ 0 \\ -1 \end{bmatrix}\right) = \left\{ \begin{bmatrix} -1 \\ 0 \\ 0 \\ -1 \end{bmatrix}, \begin{bmatrix} 0 \\ +1 \\ 0 \\ -1 \end{bmatrix}, \begin{bmatrix} 0 \\ -1 \\ 0 \\ -1 \end{bmatrix}, \begin{bmatrix} -1 \\ 0 \\ 0 \\ +1 \end{bmatrix}, \begin{bmatrix} -1 \\ 0 \\ -1 \\ 0 \end{bmatrix}, \begin{bmatrix} -1 \\ 0 \\ +1 \\ 0 \end{bmatrix} \right\}.$$

LSD-SM algorithm: The LSD-SM algorithm for SM-MIMO detection starts with an initial solution vector $\hat{\mathbf{x}}^{(0)}$ as the current solution. For example, $\hat{\mathbf{x}}^{(0)}$ can be the MMSE solution vector $\hat{\mathbf{x}}_{\text{MMSE}}$. Using the neighborhood definition in (13), it considers all the neighbors of $\hat{\mathbf{x}}^{(0)}$ and searches for the best neighbor with least ML cost which also has a lesser ML cost than the current solution. If such a neighbor is found, then it declares this neighbor as the current solution. This completes one iteration of the algorithm. This process is repeated for multiple iterations till a local minimum is reached (i.e., no neighbor better than the current solution is found). The vector corresponding to the local minimum is declared as the final output vector $\hat{\mathbf{x}}$. The non-zero entry in the kth user's sub-vector in $\hat{\mathbf{x}}$ and its index are then demapped to obtain the information bits of the kth user.

Multiple restarts: The performance of the basic LSD-SM algorithm in the above can be further improved by using multiple restarts, where the LSD-SM algorithm is run several times, each time starting with a different initial solution and declaring the best solution among the multiple runs. The proposed LSD-SM algorithm with multiple restarts is listed in **Algorithm 2**.

1: **Input** : $\mathbf{y}, \mathbf{H}$, r: no. of restarts
2: **for** $j = 1$ **to** r **do**
3: compute $\mathbf{c}^{(j)}$ (initial vector at jth restart)
4: find $\mathcal{N}(\mathbf{c}^{(j)})$
5: $\mathbf{z}^{(j)} = \underset{\mathbf{q} \in \mathcal{N}(\mathbf{c}^{(j)})}{\text{argmin}} \ \|\mathbf{y} - \mathbf{H}\mathbf{q}\|^2$
6: **if** $\|\mathbf{y} - \mathbf{H}\mathbf{z}^{(j)}\|^2 < \|\mathbf{y} - \mathbf{H}\mathbf{c}^{(j)}\|^2$ **then**
7: $\mathbf{c}^{(j)} = \mathbf{z}^{(j)}$
8: goto step 4
9: **else**
10: $\hat{\mathbf{x}}^{(j)} = \mathbf{c}^{(j)}$
11: **end if**
12: **end for**
13: $i = \underset{1 \leq j \leq r}{\text{argmin}} \ \|\mathbf{y} - \mathbf{H}\hat{\mathbf{x}}^{(j)}\|^2$
14: **Output** : $\hat{\mathbf{x}} = \hat{\mathbf{x}}^{(i)}$

Algorithm 2: Listing of the proposed LSD-SM algorithm with multiple restarts.

Complexity: The LSD-SM algorithm complexity consists of two parts. The first part involves the computation of the initial solution. The complexity for computing the MMSE initial solution is $\mathcal{O}(N^2 K n_t)$. The second part involves the search complexity, where, in order to compute the ML cost, we require to compute (i) $\mathbf{H}^H\mathbf{H}$ which has $\mathcal{O}(K^2 n_t^2 N)$ complexity, and (ii) $\mathbf{H}^H\mathbf{y}$ which has $\mathcal{O}(K n_t N)$ complexity. In addition, the complexity per iteration and the number of iterations to reach the local minima contribute to the search complexity, where the complexity per iteration is $O(K|\mathbb{S}_{n_t,\mathbb{A}}|)$. The complexity (in number of real operations) obtained from simulations are discussed in Fig. 6.

Performance: We evaluated the performance of multiuser SM-MIMO using the proposed LSD-SM algorithm and compared it with that of massive MIMO using ML detection for the same spectral efficiency. Figure 4 shows the performance comparison between SM-MIMO with ($n_t = 4$, 4-QAM) and massive MIMO with ($n_t = 1$, 16-QAM), both having 4 bpcu per user. For SM-MIMO, detection performance of both LSD-SM (presented in this section) and MPD-SM (presented in the previous section) are shown. In LSD-SM, the number of restarts used is $r = 2$. The initial vectors used in the first and second restarts are MMSE solution vector and random vector, respectively. For massive MIMO, ML detection performance using sphere decoder is plotted. It can be seen that SM-MIMO using LSD-SM and MPD-SM algorithms outperform massive MIMO using sphere decoding. Specifically, SM-MIMO using LSD-SM performs better than massive MIMO by about 5 dB at 10^{-3} BER. Also, comparing the performance of LSD-SM and MPD-SM algorithms in SM-MIMO, we see that LSD-SM performs better than MPD-SM by about 1 dB at 10^{-3} BER.

Performance as a function of loading factor: In Fig. 5, we compare the performance of SM-MIMO (with $n_t = 4$, $n_{rf} = 1$, 4-QAM) and massive MIMO (with $n_t = n_{rf} = 1$, 16-QAM), both at 4 bpcu per user, as a function of system loading factor α, at an average SNR of 9 dB. For SM-MIMO, the detectors considered are MMSE, MPD-SM, and LSD-SM. The detectors considered for massive MIMO are MMSE

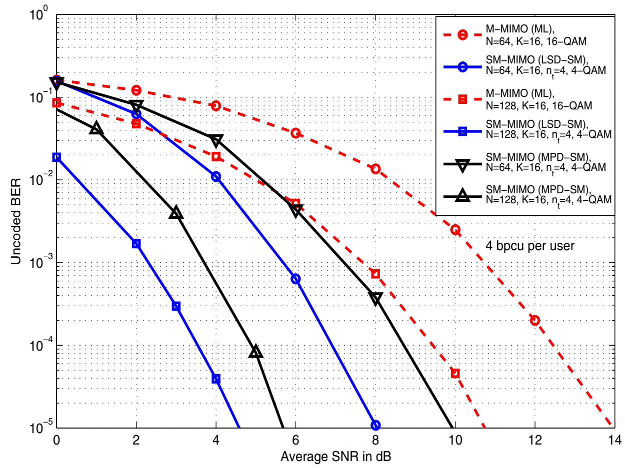


Fig. 4. BER performance of multiuser SM-MIMO ($n_t = 4$, $n_{rf} = 1$, 4-QAM) using LSD-SM and MPD-SM algorithms, and massive MIMO ($n_t = 1$, $n_{rf} = 1$, 16-QAM) using sphere decoding, at 4 bpcu per user, $K = 16$, $N = 64, 128$.

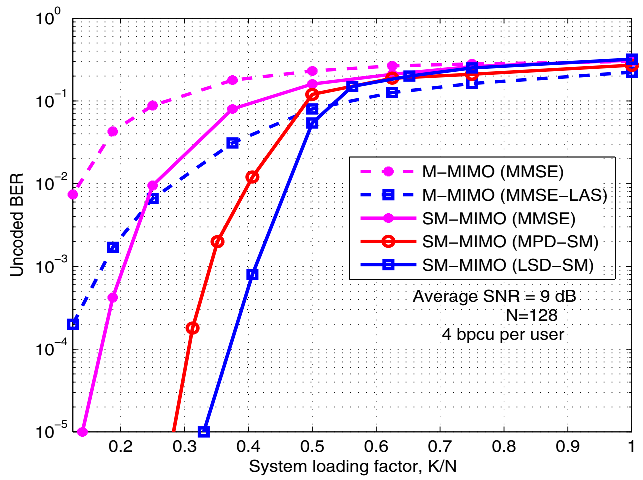


Fig. 5. BER performance of SM-MIMO ($n_t = 4$, $n_{rf} = 1$, 4-QAM) and massive MIMO ($n_t = 1$, $n_{rf} = 1$, 16-QAM) as a function of system loading factor, α. $N = 128$, SNR = 9 dB, and 4 bpcu per user.

and MMSE-LAS algorithm in [2],[3] with 2 restarts. From Fig 5, we observe SM-MIMO performs significantly better than massive MIMO at low to moderate loading factors. For the same system settings, we show the complexity plots for various SM-MIMO detectors at different loading factors in Fig. 6. It can be seen that the proposed MPD-SM detector has less complexity than MMSE detector; yet, MPD-SM detector outperforms MMSE detector (as can be seen in Fig. 5). The proposed LSD-SM detector performs better than the MPD-SM detector with some additional computational complexity (as can be seen in Fig. 6).

V. Conclusions

We proposed low complexity detection algorithms for large-scale SM-MIMO systems. These algorithms, based on message passing and local search, scaled well in complexity and achieved very good performance. An interesting observation from the simulation results is that SM-MIMO outperforms

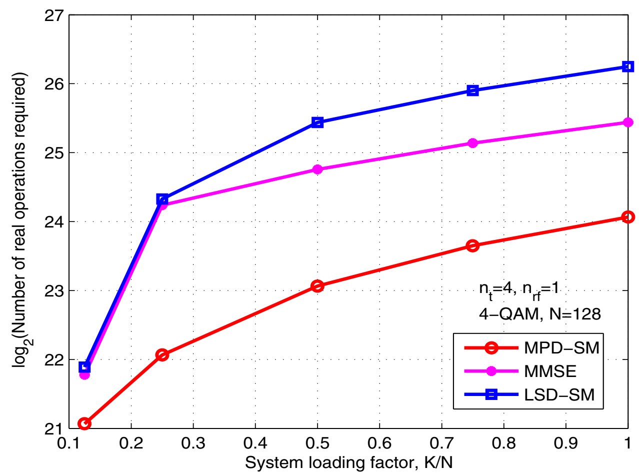


Fig. 6. Complexity comparison between MMSE, MPD-SM and LSD-SM detection algorithms in multiuser SM-MIMO as a function of system loading factor, α. $N = 128$, $n_t = 4$, $n_{rf} = 1$, 4-QAM, and 4 bpcu per user.

massive MIMO for the same spectral efficiency (with only one transmit RF chain at each user in both systems). The SNR advantage in favor of SM-MIMO is attributed to the fact that, because of the spatial index bits, SM-MIMO can achieve the spectral efficiency using a smaller sized modulation alphabet compared to that in massive MIMO.

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