Joint Active Device Identification and Symbol Detection Using Sparse Constraints in Massive MIMO Systems

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***Abstract*— In this paper, we consider a wireless system with a central station equipped with a large number of antennas surveilling a multitude of single antenna devices. The devices become active and transmit blocks of symbols sporadically. Our objective is to blindly identify the active devices and detect the transmit symbols. To this end, we exploit the sporadic nature of the device to station communication and formulate a sparse optimization problem as an integer program. Furthermore, we employ the convex relaxation of the discrete optimization variables in the problem in order reduce its computational complexity. A procedure to further lower the symbol detection errors is also discussed. Finally, the influence of system parameters on the performance of the proposed techniques is analysed using simulation results.**

I. Introduction

Massive multiple-input multiple-output (MIMO) systems, with tens or hundreds of antennas at base stations (BSs), are capable of simultaneously serving a large number of users over the same time-frequency resources with immense data rates [1–3]. Along with heterogeneous network architectures [4–6] and millimeter wave communication [7, 8], the massive MIMO technology can enhance spectral efficiency of the current wireless networks by many orders of magnitude, and justifiably it is recognized as one of the central pillars of the upcoming 5G networks [9, 10].

The application of massive MIMO technology is, however, not limited to mobile communication networks. Similar to cellular networks, the benefits of massive MIMO systems can be reaped by other wireless networks such as wireless sensor networks (WSNs), wireless sensor and actuator networks (WSANs), wireless local area networks (WLANs), industrial WLANs, wireless personal area networks (WPANs), for the purpose of process and industrial automation [11, 12], condition monitoring [13, 14], smart grid monitoring and control [15, 16], medical monitoring, to name a few. For such networks that comprise of inexpensive low-complexity low-power sensor nodes, which typically accumulate or sense some information with an objective of transmitting it to the central stations, the massive MIMO architecture is particularly beneficial. With the use of large number of antennas at the stations, beamforming techniques can be applied that significantly reduce uplink transmit powers at low-power nodes [17]. The central stations can also be empowered to blindly identify multiple active devices and communicate with them simultaneously over the same channel, thereby minimizing the signalling overhead associated with the channel access and scheduling process on the low-complexity devices. Moreover, by allowing the nodes to transmit signals at random without any need for the channel access and scheduling process, the overall latency in the system can be reduced, which is crucial for time-critical applications such as industrial automation. High spatial resolution can be achieved with the use of large number of antennas, which enables the stations to resolve closely spaced nodes [18, 19].

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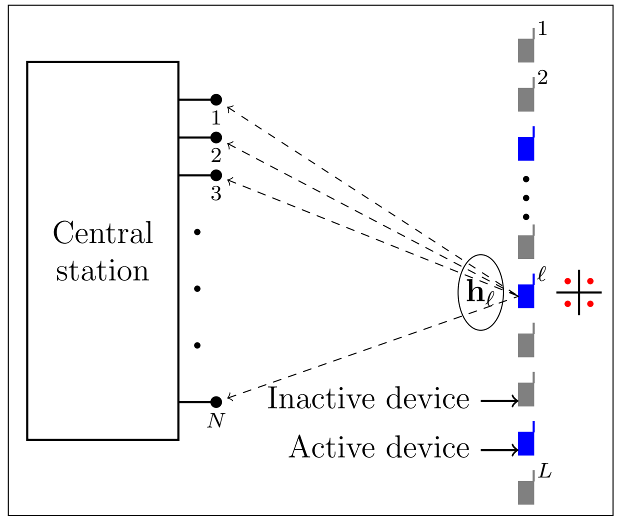

Fig. 1. Schematic diagram of the system.

In this paper, we consider a general massive MIMO network with a central station (or BS) equipped with a large number of antennas. The network also comprises single antenna devices (users, sensor nodes, etc.), which become active and transmit blocks of symbols sporadically. We exploit the sporadic nature of device to station communication and formulate a sparse optimization problem as an integer program, in order to identify the active devices and detect the transmit symbols. We further relax the integer constraints on the optimization variables to model the problem as a convex program. A procedure to further reduce the symbol error rate (SER) is discussed, for

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those networks requiring a higher link-reliability. Simulation results illustrate the suitability of the proposed method for large scale networks with high link-reliability requirements and time-critical applications.

II. System Model

We consider a co-channel uplink MIMO system with L single antenna devices communicating with a central station equipped with N receive antennas, as shown in Fig. 1. The time resource is divided into frames, with each frame comprised of T time slots. At the beginning of a frame the ℓth device wakes up randomly and independently with a probability $P_\ell \ll 1$, synchronizes to the network, and transmits a block of T symbols, for $\ell \in \mathcal{L} \triangleq \{1, 2, \ldots, L\}$. Therefore, the average number of transmitting (i.e., active) devices during any frame is given by $K = \sum_{\ell=1}^{L} P_\ell \ll L$. Each transmit symbol is assumed to be chosen independently from a constellation set $\mathcal{C} \triangleq \{c_1, c_2, \ldots, c_M\}$ with $c_m \in \mathbb{C}, m \in \mathcal{M} \triangleq \{1, 2, \ldots, M\}$. Let $\mathbf{s}_t \triangleq [s_{1,t}, s_{2,t}, \ldots s_{L,t}]^T, t \in \mathcal{T} \triangleq \{1, 2, \ldots, T\}$ be the transmit symbol vector at the tth time slot of a given frame, with $s_{\ell,t} \in \mathcal{C}$ being the transmit symbol of the ℓth device at the tth time slot if it is active and $s_{\ell,t} = 0$ otherwise. The matrix $\mathbf{S} \triangleq [\mathbf{s}_1, \mathbf{s}_2, \ldots, \mathbf{s}_T]$ denotes the transmit symbol matrix. Let $\mathbf{h}_\ell \in \mathbb{C}^{N\times 1}$ represent the channel vector between the ℓth device and the station, with the channel matrix defined as $\mathbf{H} \triangleq [\mathbf{h}_1, \mathbf{h}_2, \ldots, \mathbf{h}_L]$. The channel is assumed to be flat-fading and constant over the duration of the frame, which is a valid assumption for the sensor networks with relatively fixed positions of stations, sensor nodes, and scatterers. Furthermore, we assume that $\mathbf{H}$ is known at the station, which can be accomplished by, e.g., occasional uplink training using pilot signals [20, 21]. Any minor drift in the channel, e.g., due to clock offsets, can also be compensated by the station transmitting regular downlink pilots, and the devices performing the necessary preprocessing on the transmit symbols. In the case of line-of-sight environment, which will be typical in 5G networks due to the deployment of small cells and millimeter wave communication, the channel matrix can also be described analytically for each device [22, 23], which eliminates the training requirements.

Let $\mathbf{y}_t$ indicate the received signal vector at the central station at the tth time slot. The received signal matrix $\mathbf{Y} \triangleq [\mathbf{y}_1, \mathbf{y}_2, \ldots, \mathbf{y}_T]$ over T time slots in a given frame can be written as

$$\mathbf{Y} = \mathbf{H}\mathbf{S} + \mathbf{Z}, \tag{1}$$

where $\mathbf{Z}$ is noise matrix at the central station. All elements in $\mathbf{Z}$ are assumed to be i.i.d. circularly symmetric complex Gaussian distributed with mean zero.

III. Problem Formulation

The problem of joint active device identification and transmit symbol detection for the system described in the previous section can be formulated as an integer program as follows:

$$\min_{\mathbf{X},\mathbf{B},\mathbf{a}} \; ||\mathbf{Y} - \mathbf{H}\mathbf{X}||_F \tag{2a}$$

$$\text{s.t.} \quad x_{\ell,t} = \sum_{m=1}^{M} c_m b_{\ell,t,m}, \quad \forall \ell \in \mathcal{L}, \forall t \in \mathcal{T}, \tag{2b}$$

$$a_\ell = \sum_{m=1}^{M} b_{\ell,t,m} \leq \mathbf{1}, \quad \forall \ell \in \mathcal{L}, \forall t \in \mathcal{T}, \tag{2c}$$

$$b_{\ell,t,m} \in \{0, 1\}, \quad \forall \ell \in \mathcal{L}, \forall t \in \mathcal{T}, \forall m \in \mathcal{M}, \tag{2d}$$

where the solution matrix $\mathbf{X}^\star$ is a matrix with the element $x_{\ell,t}$ being an estimate of the transmit symbol $s_{\ell,t}$. The optimization matrix $\mathbf{B}$ is a binary matrix, with its element $b_{\ell,t,m} = 1$ if the ℓth device transmits the symbol c_m at the tth time slot and $b_{\ell,t,m} = 0$ otherwise. The binary vector $\mathbf{a}$ comprises the active device indicator a_ℓ, with $a_\ell = 1$ if the ℓth device is active during the given frame and $a_\ell = 0$ otherwise. In the above problem, $||\cdot||_F$ stands for Frobenius norm. Constraints (2b)-(2d) restrict values of symbol estimates $x_{\ell,t}, \ell \in \mathcal{L}, t \in \mathcal{T}$, to take value 0 (if the ℓth device is passive in the tth time slot) or, alternatively, one of the symbols in the constellation set $\mathcal{C}$ (if the ℓth device is active in the tth time slot).

However, due to the combinatorial nature of problem (2) its practical applicability is limited to very small networks with few time slots in the frames. In order to reduce the complexity, we exploit the sporadic nature of the device to station communication, and formulate the problem as

$$\min_{\mathbf{X},\mathbf{B},\mathbf{a}} \; ||\mathbf{Y} - \mathbf{H}\mathbf{X}||_F + \lambda \, ||\mathbf{a}||_1 \tag{3a}$$

$$\text{s.t.} \quad x_{\ell,t} = \sum_{m=1}^{M} c_m b_{\ell,t,m}, \quad \forall \ell \in \mathcal{L}, \forall t \in \mathcal{T}, \tag{3b}$$

$$a_\ell = \sum_{m=1}^{M} b_{\ell,t,m} \leq 1, \quad \forall \ell \in \mathcal{L}, \forall t \in \mathcal{T}, \tag{3c}$$

$$b_{\ell,t,m} \in \{0, 1\}, \quad \forall \ell \in \mathcal{L}, \forall t \in \mathcal{T}, \forall m \in \mathcal{M}, \tag{3d}$$

where λ denotes an appropriate weighting constant. The minimization of the ℓ_1-norm of $\mathbf{a}$ in the objective function promotes row-sparsity on $\mathbf{X}$, and thereby encourages the optimal solution to have only few active devices [24, 25], which complies with the system model. The integer programs such as problem (3) is generally solved employing continuous relaxation based procedures such as the branch-and-bound algorithm, where the discrete constraint (3d) is replaced by the continuous bound constraint $0 \leq b_{\ell,t,m} \leq 1$. In such methods, the additional ℓ_1-norm term in the objective function promotes the early pruning of non-row sparse nodes of the solution space, and thereby speeds-up the optimization process.

The complexity of the above problem can be further reduced by relaxing the search space of each transmit symbol estimate to the convex hull of constellation points in $\mathcal{C}$ [26, 27], and by minimizing the $\ell_{2,1}$-norm of $\mathbf{X}$ directly, similar to the group

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LASSO problems in [28–30]. The resultant problem is given by

$$\min_{\mathbf{X}} \; ||\mathbf{Y} - \mathbf{H}\mathbf{X}||_F + \lambda \, ||\mathbf{X}||_{2,1} \tag{4a}$$

$$\text{s.t.} \;\; x_{\ell,t} \in \text{conv}(\mathcal{C}), \quad \forall \ell \in \mathcal{L}, \forall t \in \mathcal{T}, \tag{4b}$$

where $\text{conv}(\mathcal{C})$ symbolizes the convex hull of constellation points in $\mathcal{C}$. The benefits of tailoring $\text{conv}(\mathcal{C})$ as the search space for the transmit symbol estimate $x_{\ell,t}, \ell \in \mathcal{L}, t \in \mathcal{T}$, are twofold: Firstly, the relaxation of the search space of $x_{\ell,t}$ from the discrete set $\mathcal{C}$ to the continuous convex set $\text{conv}(\mathcal{C})$ makes the problem a convex program, which can be readily solved using existing fast algorithms such as the interior-point-methods [26]. Moreover, the number of optimization variables in the problem becomes significantly smaller when compared with those in problems (2) and (3). Secondly, by restricting the search space of $x_{\ell,t}$ to $\text{conv}(\mathcal{C})$ instead of admitting a completely unconstrained search space $\mathbb{C}$, the SERs can be reduced [31, 32].

The set of indices of active devices, denoted as $\mathcal{I}$, can be obtained from the indices of non-zero rows of the optimal solution $\mathbf{X}^\star$ of problem (3) or (4), i.e.,

$$\mathcal{I} \triangleq \left\{ \ell \;\Big|\; \sum_{t=1}^{T} |x_{\ell,t}| \neq 0, \forall \ell \in \mathcal{L} \right\}. \tag{5}$$

Subsequently, the transmit symbol estimates of the ith device can be directly obtained from the elements of the ith row of $\mathbf{X}^\star$ in case of problem (3), and by projecting each element in the row to the nearest constellation point in $\mathcal{C}$, in case of problem (4).

IV. Symbol Detection Enhancement

In this section, we discuss a symbol detection enhancement (SDE) method to improve the symbol detection performance for devices that have been classified as active exerting one of the sparse optimization approaches introduced in the previous section. Let $K = |\mathcal{I}|$ be the number of active devices at a given frame. Let $\bar{\mathbf{H}}$ be the channel matrix comprising the channel vectors of active devices, i.e., $\bar{\mathbf{H}} \triangleq [\mathbf{h}_{\mathcal{I}_1}, \mathbf{h}_{\mathcal{I}_2}, \ldots, \mathbf{h}_{\mathcal{I}_K}]$, where $\mathcal{I}_k$ indicates the kth element of the set $\mathcal{I}$. Let $\bar{\mathbf{S}}$ represent the transmit symbol matrix of K active devices over the given frame. Consequently, we can rewrite Eq. (1) as

$$\mathbf{Y} = \bar{\mathbf{H}}\bar{\mathbf{S}} + \mathbf{Z}. \tag{6}$$

The optimization problem to estimate $\bar{\mathbf{S}}$ in order to minimize the SER is given by

$$\min_{\bar{\mathbf{X}}} \; \left|\left|\mathbf{Y} - \bar{\mathbf{H}}\bar{\mathbf{X}}\right|\right|_F \tag{7a}$$

$$\text{s.t.} \;\; \bar{x}_{i,t} \in \mathcal{C}, \quad \forall i \in \mathcal{I}, \forall t \in \mathcal{T}, \tag{7b}$$

where the optimal solution $\bar{\mathbf{X}}^\star \triangleq [\bar{\mathbf{x}}_1, \bar{\mathbf{x}}_2, \ldots, \bar{\mathbf{x}}_T]$ is an estimate of $\bar{\mathbf{S}}$ and $\bar{x}_{i,t}$ is an element of $\bar{\mathbf{X}}$.

Similar to problem (4), the search space of $\bar{x}_{i,t}$ can be relaxed to $\text{conv}(\mathcal{C})$ in order to reduce the computational complexity of the above problem. Moreover, since the transmit symbols of an active device at different time slots are independent of one another, the problem can be decomposed into T independent subproblems, one for each time slot, given by

$$\min_{\bar{x}_{i,t}} \; \left|\left|\mathbf{y}_t - \bar{\mathbf{H}}\bar{\mathbf{x}}_t\right|\right|_2 \tag{8a}$$

$$\text{s.t.} \;\; \bar{x}_{i,t} \in \text{conv}(\mathcal{C}), \quad \forall i \in \mathcal{I}, \tag{8b}$$

$\forall t \in \mathcal{T}$. The subproblems in problem (8) can be efficiently solved employing the low-complexity algorithm proposed in [31] when the symbols in the constellation set $\mathcal{C}$ are constant modulus, and similar approaches can be devised when symbols have different modulus.

V. Numerical Results

In this section, we compare the performance of problem (3) (named as *IP-based method*), problem (4) (named as *CP-based method*), and the conventional zero-forcing based (ZF-based) method[1], in terms of device identification error rate (DIER), SER and run-time. The DIER accounts for both false alarms (inactive devices being identified as active devices) as well as missed detections (active devices being not identified). The performance achieved by the SDE method, discussed in Section IV, is also included in the SER comparisons.

Simulations are carried out with the Rayleigh fading channel. The transmit symbols are chosen from the quadrature phase-shift keying (QPSK) constellation ($M = 4$). A weighting constant $\lambda = 0.4$ is chosen empirically for both problems (3) and (4). The optimization solver CPLEX v12.6.1 is employed to solve the IP-based method as well as the CP-based method.

Fig. 2 compares the performance of the mentioned methods for a medium scale network. From the first and second sub-figures it is apparent that the IP-based method is remarkably superior to both the CP-based and the ZF-based methods in the DIER and SER performances. However, the third sub-figure reveals that the average run-time of the IP-based method grows exponentially with the network size, due to its exponentially growing complexity, which limits the applicability of this method to only medium scale networks. On the contrary, the average run-time of the CP-based method is extremely low, and increases nominally with the network size.

Fig. 3 and Fig. 4 illustrate that the CP-based method yields strikingly low DIERs and SERs respectively, when compared with the ZF-based method, for a larger network with $N = 32$ receive antennas and $L = 64$ devices. In the first sub-figure of Fig. 3 we can notice that the DIER of the CP-based method improves significantly as the signal-to-noise-ratio (SNR) at the central station increases. The second sub-figure in Fig. 3 depicts the DIER performance of the CP-based and the ZF-based methods for various values of symbol block-size T. From the sub-figure it becomes apparent that solving the problem jointly over multiple symbols ($T > 1$) yields a superior DIER performance when compared with executing the same

[1]The ZF-based method solves the under-determined system $\mathbf{Y} - \mathbf{H}\mathbf{X} = \mathbf{0}$, and quantizes the solutions to the nearest point in a set that comprises the constellation symbols and zero.

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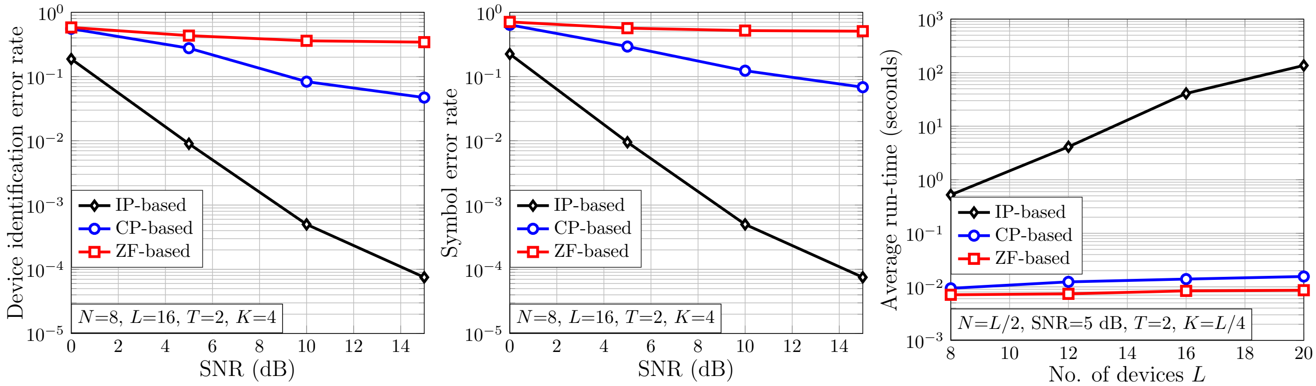

Fig. 2. Comparison of the performance and the average run-time of the various methods.

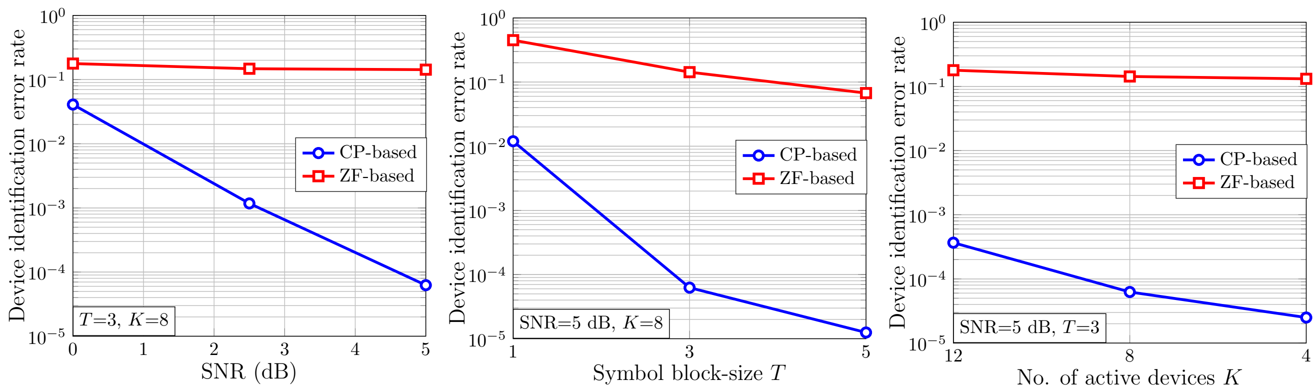

Fig. 3. Device identification error rates of the CP-based and the ZF-based methods for $N = 32$, $L = 64$.

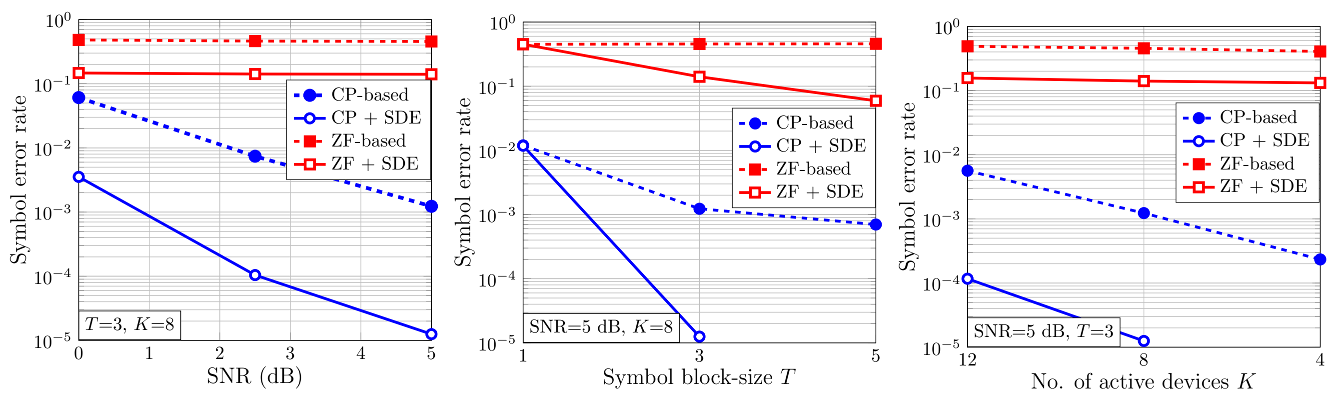

Fig. 4. Symbol error rates of the CP-based and the ZF-based methods for $N = 32$, $L = 64$.

over individual symbols ($T = 1$). In the third sub-figure we can notice that the DIER performance improves gradually as the ratio $\frac{K}{L}$ decreases due to increase in the sparsity level in the system. The sub-figures in Fig. 4 demonstrate that the SDE method reduces the SERs substantially, which highlights the effectiveness of the discussed enhancement process in achieving a higher link-reliability in wireless networks.

VI. Conclusion

Sparse optimization methods are developed for blind active device identification and symbol detection in a massive MIMO system. The proposed methods empower the central stations to identify and communicate with multiple devices simultaneously over the same channel. By eliminating the need for channel access and scheduling process the proposed methods reduce the signalling overhead and the latency in wireless networks, which are added benefits of the massive MIMO for application such as industrial automation, along with the standard massive MIMO benefits. Moreover, a symbol detection enhancement method is discussed. The simulation results show that a higher link-reliability can be achieved with the enhancement method. The run-time analysis also illustrate the suitability of the proposed methods for large scale networks with time-critical applications.

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