A Constrained Clustering-Based Blind Detector for Spatial Modulation

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***Abstract*—In this letter, we propose a novel clustering-based detector for spatial modulation multiple-input multiple-output (MIMO) system. Specifically, we first convert unconstrained optimization problem of conventional K-means algorithm to the constrained optimization by controlling the number of received symbols in each cluster. Then, a low complexity greedy algorithm is designed for solving the constrained optimization problem to determine the cluster centroids of proposed detector, and a novel detector based on the greedy algorithm is proposed accordingly. The simulation results show that proposed detector efficiently avoids the occurrence of error floor effects of conventional K-means detector and can achieve near-ML performance even if the number of clusters is large while effectively reducing the complexity compared to existing blind detectors.**

Keywords*—*blind detection; greedy algorithm; K-means clustering (KMC); spatial modulation (SM)

I. Introduction

Spatial modulation (SM) is a novel modulation concept of MIMO transmission technique [1]-[3], which aims at reducing the complexity and cost of traditional MIMO schemes. It has emerged as an attractive candidate to achieve the spectral and energy efficiency fulfillment of the next generation wireless communications and has a potential application prospect in both well-known Internet Of Things (IOT) and Wireless Sensor Network (WSN) [4].

In the SM system, although the maximum likelihood (ML) detector [5] achieves an optimal performance, its complexity is extremely high. To this end, a large number of low-complexity detection algorithms are proposed, such as signal vector based detection (SVD) detector [6], sphere decoding(SD) detector [7] and so on. The aforementioned detectors have focused on studying the bit error ratio (BER) performance over fading channels with the assumption of perfect channel state information (CSI), which is difficult to obtain and leads to a severe deterioration in achievable performance. Thus, to get rid of CSI-estimation, [4] proposed a fully blind K-means clustering (KMC) detection for the relatively low-rate space shift keying (SSK) system. Unfortunately, it is conducted multiple times to avoid the error floor caused by the local minimum, which is challenging to the computational resources, especially for high order modulation and large-scale transmit antennas. For this reason, an improved KMC (IKMC) detector and an affinity propagation (AP) detector for SM system are proposed in [8], which efficiently avoid the error floor of KMC detector. Besides, the main advantage of the AP detector that it does not need to know the number of clusters. However, on the one hand, the performance of the IKMC detector will decrease dramatically as the number of clusters increases, that is, it may be not suitable for the case where the number of clusters is large. On the other hand, the AP detector has a relatively high complexity compared to other existing clustering detectors.

Therefore, to avoid the deficiencies of KMC [4] and IKMC detectors [8], we propose a novel blind detector based on the constrained clustering concept. Firstly, the KMC's unconstrained optimization problem is transformed to a constrained optimization problem by controlling the number of received symbols in each cluster. Then, the constrained optimization problem is addressed by the low-complexity greedy algorithm proposed in this paper, which is aiming to obtain the optimized cluster centroids of proposed detector. Furthermore, a new detector combined with greedy algorithm is proposed correspondingly in this letter. Compared to conventional KMC, IKMC and AP detectors, the proposed detector is superior in detection performance as well as complexity.

II. System model

We consider an uncoded MIMO system adopting SM modulation in this section, which depends on N_t transmit antennas, N_r receive antennas and complex-valued M-ary constellations, e.g., phase-shift keying (PSK) and quadrature-amplitude modulation (QAM).

In SM, only one antenna keeps active at each time instant, and it is assumed that l-th antenna is activated, the transmitted signal vector $\boldsymbol{x}_k \in \mathbb{C}^{N_t \times 1}$ at k-th time instant as:

$$\boldsymbol{x}_k = s_l^m \boldsymbol{e}_l = [\underbrace{0, \cdots, 0}_{l-1}, s_l^m, \underbrace{0, \cdots, 0}_{N_t - l}]^T, \ s \in \ \mathbb{S} \qquad (1)$$

where $\mathbb{C}^{N_t \times 1}$ represents a $N_t \times 1$ complex set and $\boldsymbol{e}_l (1 \leqslant l \leqslant N_t)$ is an N_t-dimensional standard basis vector. It is assumed that the probability of transmitting binary bit streams 0 and 1 is equal, therefore, the probability of activating each antenna is equal, and the probability of selecting transmit symbol s_l^m drawn from constellation signal set $\mathbb{S}$ is also equal, i.e., $p(s_l^m) = \frac{1}{|\mathbb{S}|}$, where $|\mathbb{S}|$ is the cardinality of the set $\mathbb{S}$ with $|\mathbb{S}| = M$. Given the $N_t \times L$ matrix of transmitted signals as $\boldsymbol{X} = [\boldsymbol{x}_1, \cdots, \boldsymbol{x}_L]$ and the corresponding $N_r \times L$ matrix of received symbols as $\boldsymbol{Y} = [\boldsymbol{y}_1, \cdots, \boldsymbol{y}_L]$. The baseband representation at the SM-MIMO receiver is determined by:

$$\boldsymbol{Y} = \boldsymbol{H}\boldsymbol{X} + \boldsymbol{N} \tag{2}$$

Here, $\boldsymbol{H} = [\boldsymbol{h}_1, \cdots, \boldsymbol{h}_{N_t}] \in \mathbb{C}^{Nr \times Nt}$ is a block-fading complex-valued channel, where $\boldsymbol{h}_n$ is the n-th column of $\boldsymbol{H}$. Each element of $\boldsymbol{H}$ is independent and identically distributed (i.i.d) complex-valued Gaussian random variable obeying $\mathcal{CN}(0, 1)$. The channel remains invariant during the time period of a block of L symbols. $\boldsymbol{N}$ is an $(N_r \times L)$-element noise matrix, where each entry of $\boldsymbol{N}$ has the same distribution as that of $\boldsymbol{H}$.

The joint ML optimal channel and signal estimation for the system in (2) is obtained by [9]:

$$(\bar{\boldsymbol{H}}, \bar{\mathbf{X}}) = \arg \min_{\substack{\boldsymbol{H} \in \mathbb{C}^{N_r \times N_t} \\ \boldsymbol{X} \in \mathbb{X}_{SM}^L}} \|\boldsymbol{Y} - \boldsymbol{H}\boldsymbol{X}\|^2 \tag{3}$$

where $\bar{\boldsymbol{H}}$ and $\bar{\boldsymbol{X}}$ represent the optimal estimate on the channel matrix $\boldsymbol{H}$ and the transmitted signal matrix $\boldsymbol{X}$, respectively. $\mathbb{X}_{SM}$ is the transmitted signal vector and the $\mathbb{X}_{SM}^L$ is the L dimensional $\mathbb{X}_{SM}$. The $\|\cdot\|$ denotes the Frobenius norm.

III. Preliminaries

In this section, firstly, the conversion and connection between the blind detection of SM-MIMO and the clustering problem will be described, and then the optimization problem of the proposed algorithm is analysis in detail.

A. Conversion and connection

The joint ML optimization search defined in (3) can also be performed using an iterative loop first over the channel matrices $\boldsymbol{H}$ and then over all the possible transmitted signal matrix $\boldsymbol{X}$ as:

$$(\bar{\boldsymbol{H}}, \bar{\boldsymbol{X}}) = \arg \left[\min_{\boldsymbol{X} \in \mathbb{X}_{SM}^L} \left\{ \min_{\boldsymbol{H} \in \mathbb{C}^{Nr \times Nt}} \|\boldsymbol{Y} - \boldsymbol{H}\boldsymbol{X}\|^2 \right\} \right] \tag{4}$$

From the conclusions of [4][8], the optimal decision $\tilde{\boldsymbol{h}}_l$ conditioned on $\boldsymbol{X}$ can be determined by ML criterion:

$$\tilde{\boldsymbol{h}}_l = \arg \left\{ \min_{\boldsymbol{h}_l \in \mathbb{C}^{N_r \times 1}} \sum_{m=1}^{M} \sum_{\boldsymbol{y}_n \in \mathbb{I}_y^k} \left\| \boldsymbol{y}_n - s_l^m \boldsymbol{h}_l \right\|^2 \right\} \tag{5}$$

Here, $\mathbb{I}_{\boldsymbol{y}}^k$ is the set of $\boldsymbol{y}_n$ that is derived from the corresponding transmitted signal $\boldsymbol{x}_n = \boldsymbol{x}_{SM}^k \in \mathbb{X}_{SM}$, $\boldsymbol{x}_n$ is the n-th column of $\boldsymbol{X}$ and k is the index of $\boldsymbol{x}_{SM}^k = s_l^m \boldsymbol{e}_l$ in $\mathbb{X}_{SM}$.

Therefore, given the optimal estimation of the channel matrix $\tilde{\boldsymbol{H}} = [\tilde{\boldsymbol{h}}_1, \cdots, \tilde{\boldsymbol{h}}_l, \cdots, \tilde{\boldsymbol{h}}_{N_t}]$ conditioned on the $\boldsymbol{X}$ given in (5), the optimal estimate on signal in (3) can be reduced to (6):

$$\begin{aligned} \bar{\boldsymbol{X}} &= \arg \min_{\boldsymbol{X} \in \mathbb{X}_{SM}^L} \|\boldsymbol{Y} - \tilde{\boldsymbol{H}}\boldsymbol{X}\|^2 \\ &= \arg \min_{\boldsymbol{X} \in \mathbb{X}_{SM}^L} \left\{ \sum_{k=1}^{N_t M} \sum_{\boldsymbol{y}_n \in \mathbb{I}_y^k} \left\| \boldsymbol{y}_n - s_l^m \tilde{\boldsymbol{h}}_l \right\|^2 \right\} \end{aligned} \tag{6}$$

The purpose of clustering problem is to minimize the sum of K $(K = N_t M)$ clusters, which is obviously consistent with the last term in (6), and $s_l^m \tilde{\boldsymbol{h}}_l$ is the centroid of the cluster $\mathbb{I}_{\boldsymbol{y}}^k$. Therefore, the SM-MIMO blind detection problem can be mapped onto a clustering problem [4].

B. Optimization problem of proposed algorithm

To obtain the solution of (6), [4] adopts the most popular unsupervised K-means (KMC) algorithm. Fig. 1 is the received signal constellation for QPSK, where Fig. 1(a) and (c) are original received signals with different CSI, correspondingly, Fig. 1(b) and (d) are the signals obtained by the traditional KMC algorithm. The parameters of Fig. 1 are set as follows: $SNR = 12dB$, N_t=2, N_r=1, $M = 4$, L =3000. Fig. 1(b) is a "good" clustering result, i.e., each original cluster contains only a optimal cluster centroid, besides, Fig. 1 (d) is a "bad" clustering result caused by local optimum of traditional KMC.

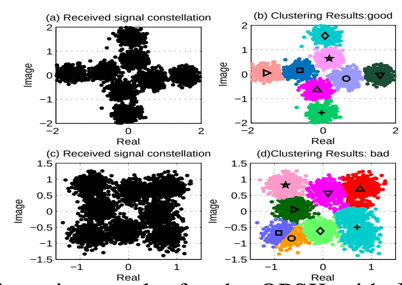

Fig. 1: Clustering results for the QPSK with N_t=2, N_r=1.

From Sec. II system model, it is known that the probability of selecting each symbol in set $\mathbb{S}$ and each antenna to active are both equal, so the number of each cluster is almost equal, i.e., L/K, which is more apparent with L increasing. We can observe from Fig. 1(b) with a "good" clustering result that the number of the received symbols in each cluster is almost equal (i.e., L/K). Compared with Fig. 1(b), it is shown from Fig. 1(d) with a "bad" clustering result that the number of received symbols in the clusters (square and circle) is about half of L/K, and the number of received symbols in the cluster (plus) is approximately twice that of L/K.

Therefore, it is concluded that the performance of KMC detector can be improved by controlling the number of received symbols in each cluster. Motivated by this, the unconstrained optimization of the traditional KMC algorithm is first transformed into the constrained optimization problem, and then it can be solved by a new greedy algorithm proposed in the next section.

Given the data set $\boldsymbol{Y} = \{\boldsymbol{y}_1, \cdots, \boldsymbol{y}_L\}$ of L points and a number K of clusters, for the original KMC algorithm, its objective function can be expressed as [10]:

$$\min_{r, \mathbf{c}} J = \sum_{n=1}^{L} \sum_{k=1}^{K} r_{nk} \|\boldsymbol{y}_n - \boldsymbol{c}_k\|^2 \tag{7}$$

where $\boldsymbol{y}_n$ is the received signal vector that only belongs to one cluster and $\boldsymbol{c}_k$ represents the cluster centroid. if $\boldsymbol{y}_n$ belongs the k-th cluster, r_{nk} is equal to 1, otherwise 0.

To avoid the phenomenon of Fig. 1(d), by adding K constraints, the unconstrained optimization (7) can be converted into the constrained optimization (8) as follows:

$$\begin{aligned} &\min_{r,\mathbf{c}} J = \sum_{n=1}^{L}\sum_{k=1}^{K} r_{nk}\|\boldsymbol{y}_n - \boldsymbol{c}_k\|^2 \\ &s.t. \ \sum_{n=1}^{L} r_{nk} = \frac{L}{K}(k = 1,\cdots K) \end{aligned} \tag{8}$$

Aiming to the optimization problem (8), we propose a greedy algorithm in next section, which is mainly to obtain the cluster centroids of the proposed detector.

IV. The Proposed Approach

The greedy algorithm is an algorithmic paradigm, which always takes the best or optimal choice at each stage with the purpose of finding a global optimum. For many problems, the greedy algorithm may not produce an optimal solution, however, it is still a good approximation of the optimal solution of optimization problem [11].

A. Greedy Strategy

The core step of the greedy algorithm is the greedy strategy, which means that the best solution to the problem can be achieved through a series of local optimal choices.

The proposed greedy algorithm based on the greedy strategy is illustrated as follows: for each received signal $\boldsymbol{y}_n$, firstly, the Euclidean distance from $\boldsymbol{y}_n$ to each cluster $\mathbb{K}^k$ is calculated, and then the distances are sorted in ascending order, where $\mathbb{K}^k$ represents the k-th cluster and satisfies the constraints of (8) (i.e., $|\mathbb{K}^k| \leqslant \frac{L}{K}(k = 1,\cdots,K)$). Moreover, the index numbers of the corresponding clusters are sequentially denoted as $\mathbb{D}_{\boldsymbol{y}_n} = \{q^1_{\boldsymbol{y}_n},\cdots,q^K_{\boldsymbol{y}_n}\}, q^k_{\boldsymbol{y}_n} \in \{1,\cdots,K\}$, that is, $\boldsymbol{y}_n$ is closest to $\mathbb{K}^{q^1_{\boldsymbol{y}_n}}$ while it is farthest to $\mathbb{K}^{q^K_{\boldsymbol{y}_n}}$. Then, the received signals $\{\boldsymbol{y}_n\}_{n=1}^L$ will be assigned in the corresponding cluster according to the greedy strategy, and it is assumed that the cluster assignment of $\{\boldsymbol{y}_n\}_{n=1}^L$ needs to be allocated a total of V rounds. Let us take the v-th $(1 \leqslant v \leqslant V)$ round of cluster assignment as an example. In general, $\boldsymbol{y}_n$ is in one of two cases:

(a) If the number of received signals contained in $\mathbb{K}^{q^v_{\boldsymbol{y}_n}}$ has not reached the upper limit L/K, that is, $|\mathbb{K}^{q^v_{\boldsymbol{y}_n}}| < \frac{L}{K}$, it is obvious that $\boldsymbol{y}_n$ is directly assigned into the nearest cluster $\mathbb{K}^{q^v_{\boldsymbol{y}_n}}$, which is most favorable for optimization of objective function J in (8).

(b) If the number of received signals included in $\mathbb{K}^{q^v_{\boldsymbol{y}_n}}$ has reached the upper limit L/K, that is, $|\mathbb{K}^{q^v_{\boldsymbol{y}_n}}| = \frac{L}{K}$. Then, if $\boldsymbol{y}_n$ can enter the cluster $\mathbb{K}^{q^v_{\boldsymbol{y}_n}}$, correspondingly, one of the received signals in the cluster $\mathbb{K}^{q^v_{\boldsymbol{y}_n}}$ must be moved out and reallocated; if $\boldsymbol{y}_n$ fails to enter the cluster $\mathbb{K}^{q^v_{\boldsymbol{y}_n}}$, then $\boldsymbol{y}_n$ will join in the next round. Therefore, we need to design a measure w to illustrate the greedy strategy of the process.

Aiming to the case (b), the measure called migration cost is introduced from (8) and is defined as:

$$\begin{aligned} w^{\boldsymbol{y}_n}_{q^v_{\boldsymbol{y}_n},q^u_{\boldsymbol{y}_n}} &= J_{q^u_{\boldsymbol{y}_n}} - J_{q^v_{\boldsymbol{y}_n}} \\ &= \|\boldsymbol{y}_n - \boldsymbol{c}_{q^u_{\boldsymbol{y}_n}}\|^2 - \|\boldsymbol{y}_n - \boldsymbol{c}_{q^v_{\boldsymbol{y}_n}}\|^2 \\ &= d^2_{nq^u_{\boldsymbol{y}_n}} - d^2_{nq^v_{\boldsymbol{y}_n}} \ , \end{aligned} \tag{9}$$

Therefore, the migration cost $w^{\boldsymbol{y}_n}_{q^v_{\boldsymbol{y}_n},q^u_{\boldsymbol{y}_n}}$ in equation (9) represents the cost of unassigned received signal $\boldsymbol{y}_n$ from cluster $\mathbb{K}^{q^v_{\boldsymbol{y}_n}}$ (the $q^v_{\boldsymbol{y}_n}$-th closest cluster to $\boldsymbol{y}_n$) to cluster $\mathbb{K}^{q^u_{\boldsymbol{y}_n}}$ (the $q^u_{\boldsymbol{y}_n}$-th closest cluster to $\boldsymbol{y}_n$) at the v-th round, and u is generally taken as $v+1$, since the migration cost $w^{\boldsymbol{y}_n}_{q^v_{\boldsymbol{y}_n},q^{v+1}_{\boldsymbol{y}_n}}$ between adjacent clusters is relatively minimal, which is most beneficial to optimize the objective function J of (8). At the v-th round of cluster assignment, it is necessary to calculate the migration cost of each received signal that has not been assigned, where the migration cost of the unassigned received signal $\boldsymbol{y}_n$ is $w^{\boldsymbol{y}_n}_{q^v_{\boldsymbol{y}_n},q^{v+1}_{\boldsymbol{y}_n}}$, and $\boldsymbol{y}_n$ is attempting to enter the cluster $\mathbb{K}^{q^v_{\boldsymbol{y}_n}}$ at the v-th round, besides, $\boldsymbol{y}_m$ has the minimum migration cost $w^{\boldsymbol{y}_m}_{q^v_{\boldsymbol{y}_n},q^{v+1}_{\boldsymbol{y}_n}}$ in the cluster $\mathbb{K}^{q^v_{\boldsymbol{y}_n}}$ at this round. Therefore, if $w^{\boldsymbol{y}_n}_{q^v_{\boldsymbol{y}_n},q^{v+1}_{\boldsymbol{y}_n}}$ is larger than $w^{\boldsymbol{y}_m}_{q^v_{\boldsymbol{y}_n},q^{v+1}_{\boldsymbol{y}_n}}$, which means that moving $\boldsymbol{y}_n$ to the adjacent cluster $\mathbb{K}^{q^{v+1}_{\boldsymbol{y}_n}}$ instead of the nearest cluster $\mathbb{K}^{q^v_{\boldsymbol{y}_n}}$ is more costly compared to $\boldsymbol{y}_m$, so $\boldsymbol{y}_n$ enters the cluster $\mathbb{K}^{q^v_{\boldsymbol{y}_n}}$ while $\boldsymbol{y}_m$ is removed from the cluster

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Algorithm 1 : The proposed detector

Input: receive sequence $\boldsymbol{Y} = \{\boldsymbol{y}_1,\cdots,\boldsymbol{y}_L\}$, $K = N_tM$

Phase I: Obtain optimized cluster centroids

1) Randomly select K received signals as the initial cluster centroids, and the upper limit of each cluster is L/K;

2) Initialize $v = 1$, $\boldsymbol{Q}^1 = \boldsymbol{Y}$

while the sequence $\boldsymbol{Q}^v$ is not empty

  Take all unassigned received signals out of $\boldsymbol{Q}^v$, for each $\boldsymbol{y}_n$, calculate its index set $\mathbb{D}_{\boldsymbol{y}_n} = \{q^1_{\boldsymbol{y}_n},\cdots,q^K_{\boldsymbol{y}_n}\}$ and the migration cost $w^{\boldsymbol{y}_n}_{q^v_{\boldsymbol{y}_n},q^{v+1}_{\boldsymbol{y}_n}}$ according to (9);

  for all unassigned received signals in $\boldsymbol{Q}^v$

  try adding $\boldsymbol{y}_n$ to the cluster $\mathbb{K}^{q^v_{\boldsymbol{y}_n}}$ in term of (i) (ii)

  (i) If the cluster $\mathbb{K}^{q^v_{\boldsymbol{y}_n}}$ has not reached the upper limit L/K, add it directly;

  (ii) If the cluster $\mathbb{K}^{q^v_{\boldsymbol{y}_n}}$ has reached the upper limit L/K, $\boldsymbol{y}_n$ is assigned to $\mathbb{K}^{q^v_{\boldsymbol{y}_n}}$ if $w^{\boldsymbol{y}_n}_{q^v_{\boldsymbol{y}_n},q^{v+1}_{\boldsymbol{y}_n}} > w^{\boldsymbol{y}_m}_{q^v_{\boldsymbol{y}_n},q^{v+1}_{\boldsymbol{y}_n}}$, where $\boldsymbol{y}_m$ has the minimal migration cost in the cluster $\mathbb{K}^{q^v_{\boldsymbol{y}_n}}$ at the v-th round, and then remove $\boldsymbol{y}_m$ from $\mathbb{K}^{q^v_{\boldsymbol{y}_n}}$, rejoin $\boldsymbol{y}_m$ to $\boldsymbol{Q}^{v+1}$; otherwise, rejoin $\boldsymbol{y}_n$ to $\boldsymbol{Q}^{v+1}$;

  end for

  $v = v + 1$;

end while

3) Update the centroids $\{\tilde{\boldsymbol{c}}_1,\cdots,\tilde{\boldsymbol{c}}_K\}$ of all clusters by calculating the mean of each cluster $\mathbb{K}^k$. If the cluster centroids no longer move or reach the maximum number of iterations, Phase I ends; otherwise, return to 2).

Phase II: Assign the received symbols

4) Obtain the optimized cluster centroids $\{\tilde{\boldsymbol{c}}_1,\cdots,\tilde{\boldsymbol{c}}_K\}$ and then assign each received signal $\boldsymbol{y}_n(n = 1,\cdots,L)$ to its closest cluster, calculate $\bar{k} = \arg\min_{k\in\{1,\cdots,K\}} ||\boldsymbol{y}_n - \tilde{\boldsymbol{c}}_k||^2$; then add $\boldsymbol{y}_n$ to the cluster $\mathbb{I}^{\bar{k}}_{\boldsymbol{y}}$;

Output: Demap $\mathbb{I}^k_{\boldsymbol{y}}(k = 1,\cdots,K)$ to information bits.

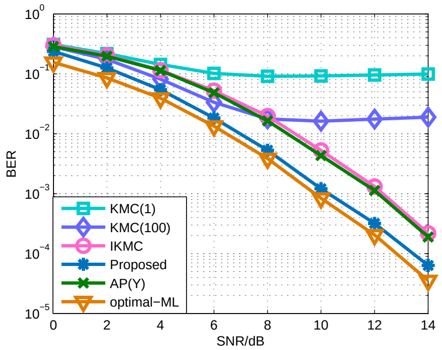

Fig. 2: BER performances of different detectors, where parameters are set as: QPSK, $N_t = 4$, $N_r = 4$, $L = 320$, the damping factor of the AP(Y) detector : λ=0.7

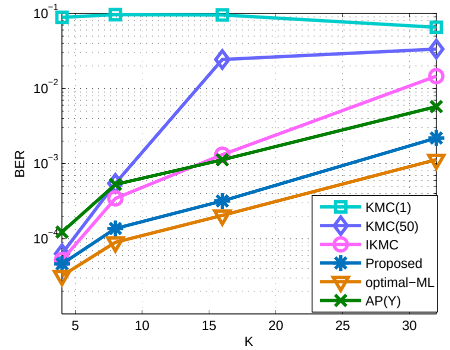

Fig. 3: The relationship between K and BER of different detectors, where parameters are set as: when $K = 4$, $L = 160$; when $K = 8$, $L = 160$;when $K = 16$, $L = 320$;when $K = 32$, $L = 640$.

$\mathbb{K}^{q^v_{\boldsymbol{y}_n}}$ and rejoins in the next round (i.e., the $(v+1)$-th round). Otherwise, $\boldsymbol{y}_n$ goes to the next round.

B. The Proposed Greedy Algorithm

Based on the greedy strategy, we propose a greedy algorithm for solving (8) (Phase I of Algorithm 1), which is aiming to determine the cluster centroids. Correspondingly, a novel detector combined with the greedy algorithm for the blind detection in the SM system is proposed, which is shown in Algorithm 1.

V. SIMULATIONS AND ANALYSIS

In this section, the simulation results of the proposed signal detection algorithm for SM-MIMO system are demonstrated. Firstly, we analyze the bit-error-rate (BER) performance of the proposed detector and compare it with traditional KMC detector [4], IKMC detector [8], AP(Y) detector [8] and the optimal ML detector in Fig. 2. Here, it is worth noting that the proposed method heavily relies on the block length L because the number of each transmitted symbol becomes more equal as the block length increases, and therefore the geometry of the transmitted constellation is exploited within the proposed algorithm in order to reduce the dependence of L, and the recommended value for the number of each cluster is generally configured to 20.

Besides, the influence of the number of clusters K on the detection performance of each detector is also investigated in Fig. 3. In the Figures, the conventional KMC algorithm with P initializations is denoted as KMC(P). Furthermore, the permutation ambiguity problem [4] of all clustering detectors, that is, the clustering results are demapped to the bits, is solved with the aid of the ideal conditions of perfect CSI in the simulation.

We can observe from Fig. 2 that the conventional KMC detector with only one initialization is trapped in the local optimum in high probability, which leads to the error floor and significant degradation in detection performance. Furthermore, this phenomenon can be alleviated by increasing the number of initializations P (i.e., KMC(P)), however, it still exists even when $P = 100$. Fortunately, IKMC and AP(Y) detectors can efficiently avoid the error floor, and the AP(Y) detector performs slightly better than the IKMC detector. However,

TABLE I: The Complexity for Different Blind Detectors. The Example are with Parameters $K = 16$,$P = 100$, $T_1 = T_4 = 4$, T_2=1,T_3=100

Detector	Choose centroids	Cluster assignment	Total complexity	Example (L=320)
KMC	$O(K)$	$O(LKT_1)$	$O(LKT_1)$	2×10^4
KMC(P)	$O(PK)$	$O(PLKT_1)$	$O(PLKT_1)$	2×10^6
IKMC	$O(L^2)$	$O(LKT_2)$	$O(L^2 + LKT_2)$	1×10^5
AP(Y)	$\backslash$	$\backslash$	$O(L^2T_3 + L^2)$	1×10^7
Proposed	$O(LKT_4)$	$O(LK)$	$O(LKT_4)$	2×10^4

there is still a large detection performance gap between IKMC detector and the optimal ML detector, and the gap becomes larger and larger with K increasing, which is verified in the Fig. 3. Therefore, IKMC detector may be not suitable for the case of large K. By contrast, it can be found that the performance of proposed detector is always very close to the optimal ML detector even if K is large.

The complexity of different detectors is shown in Table I, where T_1, T_2, T_3 and T_4 are denoted as the number of iterations of the KMC detector, IKMC detector, AP(Y) detector and the proposed detector, respectively. The specific relationship between the number of iterations of each detector is usually $T_2 < T_1 \approx T_4 < T_3$. In particular, it is observed from Table I that the complexity of the AP(Y) detector is relatively high compared with other detectors. Besides, the KMC(P) detector sacrifices the complexity to improve the performance, which imposes a significant burden on the complexity, especially for high-order modulation and large-scale transmit antennas. In addition, the complexity required for distance matrix of IKMC detector is also very high. However, the received symbols assignment of the proposed detector is only performed only once (Phase II of Algorithm 1) compared to other detectors, and therefore it has more advantages in complexity.

VI. CONCLUSION

In this letter, we investigate the problem of SM blind signal detection in MIMO systems, and then propose a blind detector based on the constrained unsupervised clustering. The simulation results confirm that the proposed detector can efficiently avoid the error floor effects of the conventional KMC detector and evade significant degradation of IKMC detector in the case of a large number of clusters. More importantly, the proposed detector outperforms the existing KMC, IKMC and AP(Y) detectors and is very close to the optimal ML detector despite its significant reduction in computational complexity.

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