A COMPRESSIVE SENSING-BASED ACTIVE USER AND SYMBOL DETECTION TECHNIQUE FOR MASSIVE MACHINE-TYPE COMMUNICATIONS

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ABSTRACT

In massive machine-type communication (mMTC) systems, a large number of machine-type devices sporadically transmit small packets with low rates. By exploiting the sporadic activity of machine-type devices, we can cast the detection problem as the compressive sensing-based multi-user detection (CS-MUD). In this paper, we propose a novel CS-MUD algorithm for the active user and symbol detection based on a maximum *a posteriori* probability (MAP) criterion. By exchanging extrinsic information between active user detector and symbol detector, the proposed algorithm improves the performance of active user detection and the reliability of symbol estimate. Numerical simulations demonstrate that the proposed algorithm achieves outstanding MUD performance.

Index Terms— massive machine-type communications, compressive sensing-based multi-user detection, maximum *a posteriori* probability.

1. INTRODUCTION

In recent years, a large number of devices are connected to the internet via wireless links [1]. In accordance with this trend, ITU defined massive machine-type communication (mMTC) as one of the important use cases for the next generation (5G) wireless systems [2]. The mMTC is distinct from human-centric communication in that mMTC traffic is *uplink-dominated* and a large number of devices *sporadically* transmit *short-sized* packets with *low* rates. Since the number of active devices is very small, that is, the transmit symbol vector is sparse, the multi-user detection (MUD) problem can be formulated as a sparse signal recovery problem. Note that when the underlying vector to be recovered is sparse, compressive sensing-based multi-user detection (CS-MUD) outperforms the classical MUD such as linear least-square (LS) and minimum mean square error (MMSE) [3].

Due to the computational benefit and competitive performance, *greedy* algorithms have been popularly used in mMTC scenarios [4–6]. The greedy algorithm iteratively finds support, i.e., the index set of non-zero elements, and then removes their vestiges from the received signal in a greedy fashion [7–9]. For details, readers are referred to [10].

In this paper, we propose a greedy algorithm that detects active devices and symbols based on a maximum *a posteriori* probability (MAP) criterion. The conventional greedy algorithms choose the index of the active device by the maximum correlation between the received vector and the column vector of the channel matrix [7–9]. However, the correlation may not be the right decision statistic, in particular, in under-determined systems where the correlation between two column vectors are large. The proposed algorithm is distinct from these approaches in that we identify the active devices using the *a posteriori* activity probability-based decision rule. Furthermore, we exploit a finite alphabet constraint (a symbol is drawn from a finite discrete alphabet) to improve the reliability of *a posteriori* symbol probability. Specifically, using the finite alphabet constraint, we compute the soft symbol information on the device activity and also what elements of the alphabet is likely to be the transmit symbol. By exchanging the extrinsic information between an active user detector and a symbol detector, the proposed algorithm improves the reliability of the soft symbol information. From the numerical evaluations, we show that the proposed algorithm outperforms conventional greedy algorithms and achieves substantial enhancement in active user and symbol detection performance.

Notation: Boldface lower and upper-case characters represent column vectors and matrices, respectively. $\mathbf{H}_{\mathcal{S}}$ ($\mathbf{h}_{\mathcal{S}}$) is the submatrix (subvector) with columns (elements) indexed by $\mathcal{S}$. $\overline{\mathcal{A}}$, $|\mathcal{A}|$, and $\mathcal{A}_j$ are the complementary set, cardinality, and j-th element of a set $\mathcal{A}$, respectively. $\mathcal{R}\{\cdot\}$ denotes the real part of the complex number. Lastly, $\{x_k\}_{k=1:K}$ represents $\{x_1, x_2, \cdots, x_K\}$.

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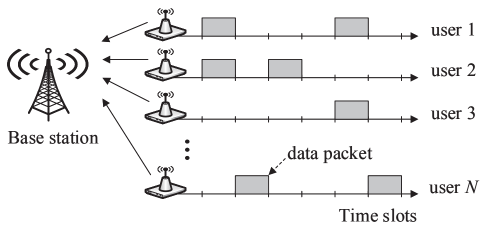


Fig. 1. The illustration of an mMTC uplink scenario.

2. SYSTEM MODEL

We consider the uplink of slot-synchronized mMTC systems where N devices (hereafter, called users) are sporadically accessing a base station (BS) on an identical time-slot basis (see Fig. 1). The symbol of each user is uniformly drawn from a finite alphabet $\mathcal{A}$ if the user is active, and zero otherwise. The symbol is then spread with a user-specific sequence with a length of M. We assume that the n-th user is active with probability of p_n and the user activities are independent of each others. In this setup, the received signal vector $\mathbf{y} \in \mathbb{C}^M$ at the BS can be described as

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{v} \tag{1}$$

where $\mathbf{H} = [\mathbf{h}_1, \mathbf{h}_2, \cdots, \mathbf{h}_N] \in \mathbb{C}^{M\times N}$ is a channel matrix capturing spreading sequences and fading channels between users and the BS, $\mathbf{x} \in \mathbb{C}^N$ is a symbol vector of all (active and inactive) users, and $\mathbf{v}$ is a complex Gaussian noise vector ($\mathbf{v} \sim \mathcal{CN}(\mathbf{0}, \sigma_v^2\mathbf{I}_M)$). In mMTC scenarios, since the system is underdetermined ($N \gg M$), it is in general not possible to recover $\mathbf{x}$. However, since only a few users are active at a time ($p_n \ll 1$), $\mathbf{x}$ can be readily modeled as a sparse vector so that $\mathbf{x}$ can be recovered by a compressive sensing technique.

3. PROPOSED MAP-BASED ACTIVE USER AND SYMBOL DETECTION

In this section, we propose MAP-based active user and symbol detection algorithm to recover the sparse symbol vector. The proposed algorithm iteratively finds an active user using a MAP-based active user detector (MAP-AUD) and then computes the soft symbol information of all detected users using a MAP-based symbol detector (MAP-SD) (see Fig. 2). By exchanging the extrinsic information (L_{E_1}/L_{E_2}) between MAP-AUD and MAP-SD, the proposed algorithm improves the performance of the active user detection and the reliability of the symbol estimate. In the sequel, the subscripts, '1' and '2', denote MAP-AUD and MAP-SD, respectively.

3.1. Symbol Activity Log-Likelihood Ratio

In this work, we use the log-likelihood ratio (LLR), which is the useful metric to extract extrinsic information from *a posteriori* information. The symbol activity LLR of a symbol x_n indicates the level on which the element of alphabet $\mathcal{A}$ is active and defined as

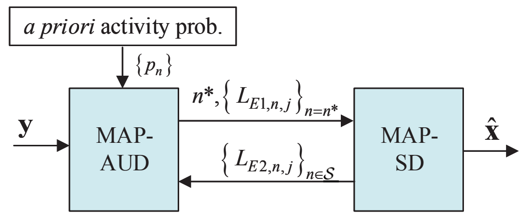


Fig. 2. The block diagram of the proposed algorithm.

$$\begin{aligned} L_{n,j}(\mathbf{y}) &= \ln \frac{P(x_n = \mathcal{A}_j \mid \mathbf{y})}{P(x_n = 0 \mid \mathbf{y})} \\ &= \underbrace{\ln \frac{P(\mathbf{y} \mid x_n = \mathcal{A}_j)}{P(\mathbf{y} \mid x_n = 0)}}_{L_{E,n,j}(\mathbf{y})} + \underbrace{\ln \frac{P(x_n = \mathcal{A}_j)}{P(x_n = 0)}}_{L_{A,n,j}} \end{aligned} \tag{2}$$

where $L_{E,n,j}$ and $L_{A,n,j}$ are the extrinsic and *a priori* components, respectively. Since $\{L_{E,n,j}\}_{j=1:|\mathcal{A}|}$ can be converted into $\{P(\mathbf{y}|x_n = \mathcal{A}_j)\}_{j=1:|\mathcal{A}|} \cup \{P(\mathbf{y}|x_n = 0)\}$ and vice versa, $\{L_{E,n,j}\}_{j=1:|\mathcal{A}|}$ can be used as extrinsic soft symbol information on x_n.

3.2. MAP-based Active User Detection

Let $\mathcal{S}$ be the support of the previous iteration, then MAP-AUD finds a support index $n^* \in \overline{\mathcal{S}}$ based on the generalized log-likelihood ratio test (GLRT) [11] and then delivers the soft symbol information $\{L_{E_1,n^*,j}\}$ to MAP-SD. That is,

$$\begin{aligned} n^* &= \arg\max_{n\in\overline{\mathcal{S}}} \left(\max_j L_{n,j}(\mathbf{y}) \right) \\ &= \arg\max_{n\in\overline{\mathcal{S}}} \left(\max_j L_{E_1,n,j}(\mathbf{y}) + L_{A_1,n,j} \right). \end{aligned} \tag{3}$$

Using *a priori* user activity probability p_n and equi-probable alphabet assumption, we have

$$L_{A_1,n,j} = \ln \frac{P(x_n \in \mathcal{A})}{|\mathcal{A}|P(x_n = 0)} = \ln \frac{p_n}{(1-p_n)} - \ln|\mathcal{A}|. \tag{4}$$

Exploiting the extrinsic symbol information on x_n ($n \in \mathcal{S}$) delivered from MAP-SD, we further have

$$\begin{aligned} & L_{E_1,n,j}(\mathbf{y}) \\ &= \ln \frac{P(\mathbf{y} \mid x_n = \mathcal{A}_j)}{P(\mathbf{y} \mid x_n = 0)} = \ln \frac{E_{\mathbf{x}_\mathcal{S}}\left[P(\mathbf{y} \mid x_n = \mathcal{A}_j, \mathbf{x}_\mathcal{S})\right]}{E_{\mathbf{x}_\mathcal{S}}\left[P(\mathbf{y} \mid x_n = 0, \mathbf{x}_\mathcal{S})\right]} \\ &\overset{(a)}{\approx} \ln \frac{E_{\mathbf{x}_\mathcal{S}}\left[\exp\left(-\left\|\mathbf{y} - \mathbf{H}_\mathcal{S}\mathbf{x}_\mathcal{S} - \mathcal{A}_j\mathbf{h}_n\right\|^2_{\mathbf{C}_n^{-1}}\right)\right]}{E_{\mathbf{x}_\mathcal{S}}\left[\exp\left(-\left\|\mathbf{y} - \mathbf{H}_\mathcal{S}\mathbf{x}_\mathcal{S}\right\|^2_{\mathbf{C}_n^{-1}}\right)\right]} \end{aligned}$$

$$\overset{(b)}{\approx} \ln \frac{\exp\left(E_{\mathbf{x}_{\mathcal{S}}}\left[-\left\|\mathbf{y}-\mathbf{H}_{\mathcal{S}}\mathbf{x}_{\mathcal{S}}-\mathcal{A}_j\mathbf{h}_n\right\|^2_{\mathbf{C}_n^{-1}}\right]\right)}{\exp\left(E_{\mathbf{x}_{\mathcal{S}}}\left[-\left\|\mathbf{y}-\mathbf{H}_{\mathcal{S}}\mathbf{x}_{\mathcal{S}}\right\|^2_{\mathbf{C}_n^{-1}}\right]\right)}$$

$$= \mathcal{R}\left\{\left(2\mathcal{A}_j\left(\mathbf{y}-\mathbf{H}_{\mathcal{S}}E[\mathbf{x}_{\mathcal{S}}]\right)-|\mathcal{A}_j|^2\mathbf{h}_n\right)^H\mathbf{C}_n^{-1}\mathbf{h}_n\right\} \quad (5)$$

where (a) is from the Gaussian approximation of the interference and (b) is from the assumptions that the support indices chosen in the previous iterations are perfect and the symbol detection errors are also negligible. Under these assumptions, $E_{\mathbf{x}}[\exp(f(\mathbf{x}))] \approx \exp(f(\mathbf{x}^*)) \approx \exp(E_{\mathbf{x}}[f(\mathbf{x})])$ where $\mathbf{x}^*$ is the symbol estimate in the previous iterations. In (5), the covariance matrix of the interference-plus-noise vector is

$$\mathbf{C}_n = \text{Cov}\left(\mathbf{H}_{\overline{\mathcal{S}}}\mathbf{x}_{\overline{\mathcal{S}}} - x_n\mathbf{h}_n + \mathbf{v}\right), \quad (6)$$

and using the extrinsic information delivered from MAP-SD, $E[\mathbf{x}_{\mathcal{S}}]$ is expressed as

$$E[x_n] = \sum_{j=1}^{|\mathcal{A}|} P(x_n = \mathcal{A}_j)\mathcal{A}_j = \frac{\sum_{j=1}^{|\mathcal{A}|}\exp(L_{E_2,n,j})\mathcal{A}_j}{1+\sum_{j=1}^{|\mathcal{A}|}\exp(L_{E_2,n,j})}. \quad (7)$$

From (4) and (5), we can find the support index n^* and obtain the soft symbol information on x_{n^*} (i.e., $\{L_{E_1,n^*,j}\}$) to be delivered to MAP-SD. Note that only extrinsic information is delivered to MAP-SD. This extrinsic information is used as *a priori* information for MAP-SD to update the soft symbol information of the previously detected symbols.

3.3. MAP-based Symbol Detection

MAP-SD updates the soft symbol information on x_n $(n \in \mathcal{S})$. Let $\mathcal{T}_n$ be $\mathcal{S} \cup \{n^*\} - \{n\}$. Similar to MAP-AUD, MAP-SD re-calculates $L_{E_2,n,j}$ $(n \in \mathcal{S})$ as

$$\begin{aligned} &L_{E_2,n,j}(\mathbf{y}) \\ &= \ln\frac{P(\mathbf{y}\mid x_n=\mathcal{A}_j)}{P(\mathbf{y}\mid x_n=0)} = \ln\frac{E_{\mathbf{x}_{\mathcal{T}_n}}\left[P(\mathbf{y}\mid x_n=\mathcal{A}_j,\mathbf{x}_{\mathcal{T}_n})\right]}{E_{\mathbf{x}_{\mathcal{T}_n}}\left[P(\mathbf{y}\mid x_n=0,\mathbf{x}_{\mathcal{T}_n})\right]} \\ &\approx \mathcal{R}\left\{\left(2\mathcal{A}_j\left(\mathbf{y}-\mathbf{H}_{\mathcal{T}_n}E[\mathbf{x}_{\mathcal{T}_n}]\right)-|\mathcal{A}_j|^2\mathbf{h}_n\right)^H\mathbf{\Gamma}^{-1}\mathbf{h}_n\right\} \end{aligned} \quad (8)$$

where

$$\mathbf{\Gamma} = \text{Cov}\left(\mathbf{H}_{\overline{\mathcal{S}}}\mathbf{x}_{\overline{\mathcal{S}}} - x_{n^*}\mathbf{h}_{n^*} + \mathbf{v}\right). \quad (9)$$

By denoting $L_{E_2,n,j}$ of the previous iteration as $\widetilde{L}_{E_2,n,j}$, we have

$$E[x_n] = \begin{cases} \frac{\sum_{j=1}^{|\mathcal{A}|}\exp(L_{E_1,n,j})\mathcal{A}_j}{1+\sum_{j=1}^{|\mathcal{A}|}\exp(L_{E_1,n,j})} & \text{if } n=n^*, \\ \frac{\sum_{j=1}^{|\mathcal{A}|}\exp(\widetilde{L}_{E_2,n,j})\mathcal{A}_j}{1+\sum_{j=1}^{|\mathcal{A}|}\exp(\widetilde{L}_{E_2,n,j})} & \text{otherwise.} \end{cases} \quad (10)$$

Note that the soft symbol information $\{L_{E_2,n,j}\}_{n\in\mathcal{S}}$ is refined by MAP-SD since $x_{n^*}\mathbf{h}_{n^*}$ is cancelled from the total interference (see (9)). After updating the soft symbol information only on x_n $(n \in \mathcal{S})$, the support index n^* and $\{L_{E_1,n^*,j}\}$ are added to $\mathcal{S}$ and $\{L_{E_2,n,j}\}$, respectively. The augmented soft symbol information is fed back to MAP-AUD for the next iteration.

3.4. Interference-Plus-Noise Covariance Matrices

In computing $L_{E_1,n,j}$ in (5) and $L_{E_2,n,j}$ in (8), we need to compute the inverse of $\mathbf{C}_n$ and $\mathbf{\Gamma}$ (see (6) and (9)). Since this computation is too burdensome, we approximate the covariance matrices as diagonal matrices. Let l be the iteration index, then under the assumption that the user-specific spreading sequence is randomly generated, we can easily show that

$$\begin{aligned} \mathbf{\Gamma}^{(l)} &= \text{Cov}\left(\mathbf{H}_{\overline{\mathcal{S}}^{(l-1)}}\mathbf{x}_{\overline{\mathcal{S}}^{(l-1)}} - x_{n^*}\mathbf{h}_{n^*} + \mathbf{v}\right) \\ &= \sum\nolimits_{n\in\overline{\mathcal{S}}^{(l)}} \beta_n\mathbf{h}_n\mathbf{h}_n^H + \sigma_v^2\mathbf{I}_M \\ &\approx \text{diag}\left(\sum\nolimits_{n\in\overline{\mathcal{S}}^{(l)}} \beta_n\mathbf{h}_n\mathbf{h}_n^H\right) + \sigma_v^2\mathbf{I}_M \\ &= \sum\nolimits_{n\in\overline{\mathcal{S}}^{(l)}} \beta_n\text{diag}\left(\mathbf{h}_n\mathbf{h}_n^H\right) + \sigma_v^2\mathbf{I}_M \end{aligned} \quad (11)$$

where $\beta_n = E[|x_n|^2] = (1/|\mathcal{A}|)\sum_{j=1}^{|\mathcal{A}|} p_n|\mathcal{A}_j|^2$ and diag$(\cdot)$ is a diagonal matrix only with diagonal elements. Using this diagonal approximation, we have

$$\begin{aligned} \mathbf{\Gamma}^{(0)} &= \text{diag}\left(\mathbf{H}\mathbf{B}\mathbf{H}^H\right) + \sigma_v^2\mathbf{I}_M, \\ \mathbf{C}_n^{(l)} &= \mathbf{\Gamma}^{(l-1)} - \beta_n\text{diag}\left(\mathbf{h}_n\mathbf{h}_n^H\right), \\ \mathbf{\Gamma}^{(l)} &= \mathbf{C}_{n^*}^{(l)}, \end{aligned} \quad (12)$$

where $\mathbf{B} = \text{diag}\left([\beta_1, \beta_2, \cdots, \beta_N]^T\right)$. Since all of $\mathbf{C}_n^{(l)}$ and $\mathbf{\Gamma}^{(l)}$ are diagonal, it is easy to inverse them.

The iteration lasts until all active users are detected. After completing the iteration, we decide $\widehat{\mathbf{x}}$; $\widehat{x}_n = \mathcal{A}_{j_n^*}$ where $j_n^* = \arg\max_j L_{E_2,n,j}$ if $n \in \mathcal{S}$, and 0 otherwise. The proposed algorithm is summarized in Algorithm 1.

4. NUMERICAL RESULTS

We simulate an under-determined mMTC system with $N = 128$ users and unit-norm random spreading sequences with a length of $M = 64$. We consider frequency-flat Rayleigh fading channels between users and the BS from $\mathcal{CN}(0,1)$. We set the activities of all users to 0.05 (i.e., $p_n = 0.05$). Data symbols are modulated by BPSK. We assume that the BS has perfect knowledge of the channel matrix $\mathbf{H}$. We stop the iteration when $\|\mathbf{r}^{(l+1)} - \mathbf{r}^{(l)}\| < 10^{-4}$ or the number of iterations reaches 16. Note that $\mathbf{r}^{(l)} = \mathbf{y} - \mathbf{H}_{\mathcal{S}^{(l)}}E[\mathbf{x}_{\mathcal{S}^{(l)}}]$ (see (5)). As a performance measure, we use the successful AUD probability and the net symbol error rate (SER) which corresponds to the SER of active users.

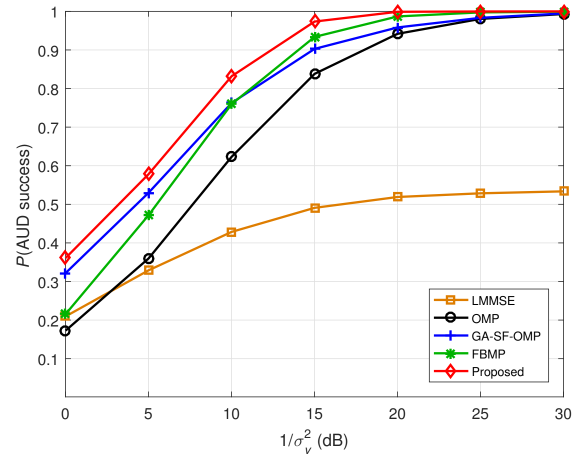
Algorithm 1 MAP-based Active User and Symbol Detection

Input: $\mathbf{y}, \mathbf{H}, \mathcal{A}, \sigma_n^2, \{p_n\}_{n=1}^{N}$
Output: $\hat{\mathbf{x}}$

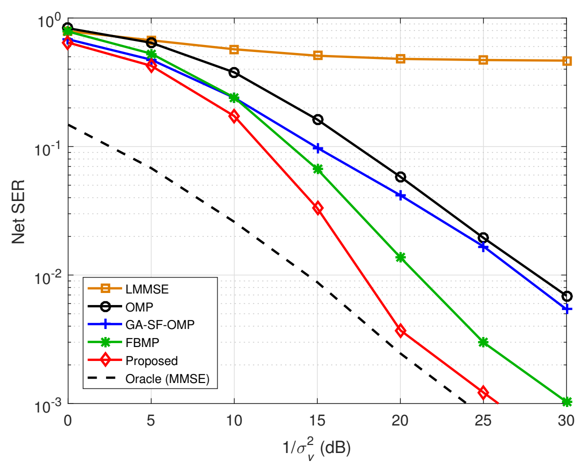
// Initialization
$\mathcal{S}^{(0)} = \varnothing,\ \{L_{E_2,n,j}\} = \varnothing,\ l = 0$
$\mathbf{\Gamma}^{(0)} = \mathrm{diag}(\mathbf{H}\mathbf{B}\mathbf{H}^H) + \sigma_v^2 \mathbf{I}_M$ // See (12).
repeat
  $l = l + 1$
  // MAP-based Active User Detection
  for $n \in \overline{\mathcal{S}}^{(l-1)}$ **do**
    $\mathbf{C}_n^{(l)} = \mathbf{\Gamma}^{(l-1)} - \beta_n \mathrm{diag}(\mathbf{h}_n \mathbf{h}_n^H)$
    for $j = 1, \cdots, |\mathcal{A}|$ **do**
      $L_{E_1,n,j}$ // See (7) for $E[\mathbf{x}_{\mathcal{S}}]$.
      $= \mathcal{R}\left\{\left(2\mathcal{A}_j\left(\mathbf{y} - \mathbf{H}_{\mathcal{S}} E[\mathbf{x}_{\mathcal{S}}]\right) - |\mathcal{A}_j|^2 \mathbf{h}_n\right)^H \mathbf{C}_n^{-1} \mathbf{h}_n\right\}$
    end for
  end for
  $n^* = \arg\max_{n \in \overline{\mathcal{S}}} \left((\max_j L_{E_1,n,j}) + \ln p_n/(1 - p_n)\right)$
  // MAP-based Symbol Detection
  $\mathbf{\Gamma}^{(l)} = \mathbf{C}_{n^*}^{(l)}$
  for $n \in \mathcal{S}^{(l-1)}$ **do**
    $\mathcal{T}_n = \mathcal{S}^{(l-1)} \cup \{n^*\} - \{n\}$
    for $j = 1, \cdots, |\mathcal{A}|$ **do**
      $L_{E_2,n,j}$ // See (10) for $E[\mathbf{x}_{\mathcal{S} \cup \{n^*\}}]$.
      $= \mathcal{R}\left\{\left(2\mathcal{A}_j\left(\mathbf{y} - \mathbf{H}_{\mathcal{T}_n} E[\mathbf{x}_{\mathcal{T}_n}]\right) - |\mathcal{A}_j|^2 \mathbf{h}_n\right)^H \mathbf{\Gamma}^{-1} \mathbf{h}_n\right\}$
    end for
  end for
  // Augmentation
  $\mathcal{S}^{(l)} = \mathcal{S}^{(l-1)} \cup \{n^*\}$,
  $\{L_{E_2,n,j}\}^{(l)} = \{L_{E_2,n,j}\}^{(l-1)} \cup \{L_{E_1,n^*,j}\}$
until stop conditions are met.
// Final result
$$\widehat{x}_n = \begin{cases} \mathcal{A}_{j_n^*} \text{ where } j_n^* = \arg\max_j L_{E_2,n,j} & \text{if } n \in \mathcal{S}, \\ 0 & \text{otherwise.} \end{cases}$$

We compare the proposed algorithm with Linear MMSE (LMMSE), Orthogonal Matching Pursuit (OMP) [7], Soft-feedback OMP (SF-OMP) [12], and Fast Bayesian Matching Pursuit (FBMP) [13]. In particular, we use Genie-Aided SF-OMP (GA-SF-OMP) with perfect knowledge of the interference variance in each iteration. As a lower bound, we use the performance of the Oracle MMSE detector which perfectly knows the support of $\mathbf{x}$. Note that the proposed algorithm, GA-SF-OMP, and FBMP exploit *a priori* user activity probabilities.

Fig. 3 (a) shows the AUD success probability. We observe that the proposed algorithm outperforms the other algorithms under test. LMMSE shows very poor performance because the system is under-determined. Overall, algorithms exploiting *a priori* user activity probabilities exhibit better performance than those without exploiting it. In Fig. 3 (b), we plot the net SER. We observe that the net SER of the proposed algorithm are much smaller than those of the other algorithms. In particular, the performance gap increases in the high SNR regime because our assumption (the previous detection of active users and symbols are perfect) becomes accurate.



(a)



(b)

Fig. 3. Performances of the proposed algorithm: (a) AUD success probability, (b) Net SER.

5. CONCLUSION

In this paper, we proposed a novel MAP-based active user and symbol detector for mMTC systems. The proposed algorithm finds the active users and detects the symbol in a greedy fashion by exploiting the sparsity of the actually active users in mMTC system The proposed scheme consists of MAP-AUD and MAP-SD. By exchanging extrinsic information between each other, the proposed algorithm improves the performance of the active user detection and the reliability of the symbol estimate. We have demonstrated that our proposed algorithm achieves a substantial gain over conventional greedy algorithms.

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