Bayesian Joint Activity and Channel Estimation for Massive Machine Type Communications

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Abstract

In this paper, we propose a novel method to jointly estimate the activities and channel coefficients of massive machine-type communications (mMTC) devices. We formulate a maximum a posteriori probability (MAP) estimation problem using the prior information including the channel distribution and device activity probability. The formulated MAP problem is solved by a greedy algorithm, named bayesian orthogonal matching pursuit (BOMP). We observe that the channel estimation performance is improved compared to the conventional channel estimation methods.

I. Introduction

Massive machine-type communications (mMTC) enable a broad range of applications including environmental monitoring, healthcare, and home automation. As the term implies, mMTC is about a massive access of machine-type devices, each with sporadic traffic [1]. With the sporadic nature of mMTC traffic, the multi-user detection problem is formulated as compressed sensing based multi-user detection (CS-MUD). In CS-MUD, the activity and data of devices are jointly detected [2]. However, most works in CS-MUD assume that the channel is perfectly known to the base station. In practice, the channel should be explicitly estimated before the detection.

In this regard, the joint activity and channel estimation method has been studied in [3]. The activities and channel coefficients of devices are estimated via Orthogonal Matching Pursuit (OMP) algorithm. However, OMP algorithm do not exploit the prior information including the channel distribution and device activity probability. In this paper, we propose a bayesian activity and channel estimation scheme by exploiting the prior distribution of the channel and activities of devices. We show by numerical simulations that proposed scheme outperforms the conventional scheme in terms of the channel estimation performance.

II. System model

We consider the uplink of MTC systems with $K$ devices as shown in Fig.1. The symbols of devices are spread with device-specific pilot code sequences with a length of $N$. Each device sporadically transmits a data symbol to the base station with activity probability $p_a$; otherwise inactive. The received signal at the base station can be described as

$$y = Sha + w = Sha + w$$

where $S$ is a $N \times K$ matrix of Gaussian random pilot sequences of $K$ devices. $w$ is $N \times 1$ noise vector with $N \sim (0, \sigma_w^2)$. $h$ denotes $K \times K$ diagonal matrix of channel coefficients and $a$ denotes $K \times 1$ sparse vector of activity pattern. Hence, $H$ is $K \times 1$ sparse vector which has a nonzero channel coefficients only for the active devices.

![Fig.1. The uplink mMTC system with sporadic activities](image)

We suppose $h$ and $a$ obey the following Bernoulli and Gaussian probabilistic model respectively as

$$p(a) = \prod_{k=1}^{K} p(a_k),$$

$$p(h) = \prod_{k=1}^{K} p(h_k),$$

where $a_k \sim \text{Ber}(p_a)$ and $h_k \sim \mathcal{N}(0, \sigma_h^2)$.

III. Proposed Scheme

In this section, we formulate a MAP problem and introduce a BOMP algorithm [4] to solve the problem.

With perfect knowledge of $S$ and distribution of $h$ and $a$, the MAP detection problem to estimate $h$ and $a$ can be formulated as follows
\[
(h, \hat{a}) = \arg \max_{(h,a)} \log p(y, h, a),
\]
(5)

To find the support \( \hat{a} \) and the coefficients \( \hat{h} \), which maximizes the cost function in (5), we define the following function:

\[
\rho^{(n)}(h_j, a_j) = \sigma^2 \log p(y, \hat{h}, \hat{a}_j),
\]
(6)

where the index \( n \) (\( n=1,2,\ldots \)) denotes the iteration count. By applying Bayes’ rule, (6) can be rewritten as,

\[
rho^{(n)}(h_j, a_j) = \sigma^2 \log p(y|\hat{h}|a_j) + \log p(\hat{h}) + \log p(\hat{a}_j) + \log \rho(\hat{a}_j)
\]
\[ - \sigma^2 \| r + (\hat{a}_j, h_j) - h_j^* \|^2 - \lambda \hat{a}_j, \]
(7)

where \( r = y - Sh \), \( \sigma = \sigma^2 \), \( \lambda = 2\sigma^2 \log((1 - p_c)/p_a) \).

The BOMP algorithm updates the support and coefficient candidates that maximize the objective function defined in (7).

We first derive the analytical expression of coefficient candidates which maximizes (7) as follows using the convexity of \( \rho^{(n)}(h_j, a_j) \).

\[
h^{(n)}_j = a_j \frac{\sigma^2}{\sigma^2 + \sigma} \left[ h^{(n-1)}_j - \left( \frac{r^{(n)}_j}{S^*_a} \right) \right].
\]
(8)

To determine the support candidates, we conduct a hypotheses test as follows

\[
\begin{cases} 
\begin{align*}
\hat{a}_j & = \begin{cases} 
(\hat{a}_j) & \text{if } j = \arg \max \rho^{(n)}(a_j, \hat{h}_j) \\
(\hat{a}_j^{(n-1)}) & \text{otherwise}
\end{cases} 
\end{align*}
\end{cases}
\]
(9)

Then, among the found support candidates, we select one candidate and the corresponding channel coefficient that maximizes the objective function (7). Then the selected index is newly incorporated into the support set as

\[
\hat{a}_j = \begin{cases} 
\begin{align*}
\hat{a}_j & = \begin{cases} 
(\hat{a}_j) & \text{if } j = \arg \max \rho^{(n)}(a_j, \hat{h}_j) \\
(\hat{a}_j^{(n-1)}) & \text{otherwise}
\end{cases} 
\end{align*}
\end{cases}
\]
(10)

Finally, the channel coefficients are updated for the active devices and for non-active devices, the coefficients are set to 0.

\[
h^{(n)}_j = \begin{cases} 
\begin{align*}
\begin{cases} 
S^*_a \rho^{(n)}(h_j) + \frac{\sigma^2}{\sigma} \mathbf{1}_k \end{cases} & \text{if } j = \arg \max \rho^{(n)}(a_j, \hat{h}_j) \\
0 & \text{otherwise}
\end{cases}
\end{align*}
\end{cases}
\]
(11)

IV. Numerical Results

We perform numerical simulations to demonstrate the effectiveness of the proposed scheme. We simulate an uplink mMTC system with \( p_a = 0.1 \), \( N = 50 \) and \( K = 100 \). We set \( \sigma^2_a = 1 \) and \( \sigma^2_a = 10^{-3} \).

Fig.2 shows the normalized mean squared error (NMSE) performances of minimum mean squared error (MMSE) estimator, OMP, BOMP and Oracle MMSE. Oracle MMSE is used as a lower bound of channel estimation algorithms. We can observe that BOMP outperforms OMP throughout the given SNR region. The gap between BOMP and OMP is due to the fact that BOMP utilizes the prior information.

Fig.3 shows the average activity error rate (AER) of OMP and BOMP. The AER performance of BOMP is better than that of OMP because BOMP.

![Fig 2. NMSE vs. average SNR](image)

![Fig 3. Average AER vs. average SNR](image)

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References


