Voting-based UE Detection Methods for Sparse Coded Multiple Access

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應用於稀疏碼多重存取技術之基於投票決策之用戶偵測方法

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摘要

相較於傳統的正交多工存取(Orthogonal Multiple Access, OMA)，非正交多工存取(Non-Orthogonal Multiple Access, NOMA)技術已被理論證實可達更好的系統傳輸率，也因此為第五代行動通訊標準視為多工存取技術選項。在此趨勢下，我們於論文考量一種特定的碼域非正交多工存取架構，稱之為稀疏碼多重存取技術。稀疏碼多重存取技術是一種多維度、基於碼表的非正交展延技術，且可運用迭代訊息傳遞演算法(Message Passing Algorithm, MPA)於接收端還原資料。

在稀疏碼多重存取架構下，此篇博士論文專注於上行無授權稀疏碼多重存取應用場景下的用戶偵測，並提出三種基於投票決策之用戶偵測方法，以及一種聯合迭代訊息傳遞演算法的效能強化方法。基於一般化概似檢驗(Generalized Likelihood Ratio Tests, GLRT)，我們的模擬結果顯示所提出的基於投票決策之用戶偵測方法可有效的偵測用戶是否正於傳遞資料狀態還是於待機狀態，提供精確的正傳遞資料用戶的表列給訊息傳遞演算解碼器。
Voting-based UE Detection Methods for Sparse Coded Multiple Access

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Abstract

The non-orthogonal multiple access (NOMA) technique can theoretically achieve a better throughput than the conventional orthogonal multiple access (OMA) technique and hence has been considered as a basic multiple access technique in the 5G standard. Along this trend, we consider a code-domain NOMA system in this thesis, which is referred to as the sparse code multiple access (SCMA). The SCMA adopts a multi-dimensional codebook-based non-orthogonal spreading technique and can use the iterative message passing algorithm (MPA) to recover the data stream at the receiver.

Under the SCMA framework, this thesis focuses on user equipment (UE) detection in the uplink grant-free SCMA scenario and proposed three voting-based strategies as well as a joint message passing algorithm (JMPA) enhancement for UE detection. Based on the generalized likelihood ratio test (GLRT), our simulation results show that the proposed voting strategies are capable of effectively detecting the statuses of UEs from either activeness or inactiveness, and can provide an accurate active UE list to the MPA decoder.
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Chapter 1

Introduction

1.1 Background

The fifth generation (5G) wireless networks are expected to meet the demands of high throughput, low latency, low control signaling overhead, and massive connectivity that supports a large number of devices. Among the three major scenarios targeted by 5G, massive machine type communication (mMTC) is the one to fulfill the massive connectivity requirement of applications like Internet of Things (IoT), as the current long term evolution (LTE) system is not able to provide such massive connectivity, especially in the uplink (UL).

This brings up the demand of high spectral efficiency for massive connectivity, and pushes the development of the new technology of non-orthogonal multiple access (NOMA) [1]. Different from the conventional orthogonal multiple access (OMA) technology, NOMA can accommodate more users via non-orthogonal resource allocation. It allows system overloading and hence supports more connections than the number of subcarriers. Thus, it is a promising technology to make feasible the realization of massive connectivity.

At this background, sparse code multiple access (SCMA) [2] was proposed to be a code-domain NOMA scheme. Under SCMA, the incoming data streams are mapped to complex codewords through a predefined sparse codebook. The sparse codebook can co-
exist with the orthogonal frequency division multiple access (OFDMA). By the sparsity of codewords, the receiver can apply iterative message passing algorithm (MPA) to recover the data streams and reach a near-optimal detection performance with a moderate complexity.

On the other hand, in order to reduce the transmission latency as well as the overhead associated with control signals for scheduling, UL grant-free multiple-access transmission [3] is proposed for IoT applications. In the UL grant free multiple-access scenario, user equipments (UEs) can transmit data in a number of pre-configured resources, which comprise times, frequencies, codebooks, or pilots. As a result, the data transmission can be launched without the request-and-grant procedure. The realization, however, requires a receiver with the following two capabilities:

1. Blind detection for active UEs with reasonable complexity and low mis-detection probability;
2. Blind decoding of users' data based on the blind-detected active UE list.

As it turns out, the accuracy of active UE detection will significantly affect the efficiency of the data retrieval of the MPA decoder. This motivates our study on the UE detection approaches in this thesis.

1.2 Motivation

Adding a demodulation reference signal (DMRS) in UE transmissions is a direct way for the receiver to determine the active UE list. Along this direction, an active UE detector (AUD) module was proposed in [4] to detect active UEs in an SCMA-based UL grant-free scenario. By utilizing orthogonal pilots for different UEs, the proposed AUD module detects the status of each UE and produces an active UE list. Afterwards, the joint message passing algorithm (JMPA) was proposed to eliminate the falsely detected active UEs and decode the data of active UEs.

Later, a refined AUD (RAUD) module was introduced to enhance the active UE detection accuracy at the receiver [5]. Further, a two-step AUD scheme that contains
RAUD module as its component was proposed. Through analyzing the difference between the characteristic values of UEs obtained in two steps, the RAUD module can correct the statuses of UEs that the AUD module misinterpreted.

Both of the above two blind detection methods require DMRSs. In the UL grant-free scenario, however, there are chances that different UEs select identical DMRS, causing erroneous detection at the base station. In addition, the number of orthogonal DMRSs is limited and may be unable to support simultaneously massive number of active UEs. Even if a sufficient number of orthogonal DMRSs could be provided, adding DMRS in the UE transmission may considerably waste the resources and boost the system overhead, particularly in the scenarios of mMTC and URLLC (Ultra-reliable and low latency communication), where a bulky number of small packets are possibly transmitted. Consequently, such pilot-aided blind detection not only reduces the flexibility of resource allocation but weakens the overloading capability of NOMA schemes.

As an alternative approach, we consider a blind UE detection without pilots in this thesis. Specifically, we propose a voting-based UE detection method for SCMA. By using the generalized likelihood ratio test (GLRT) based on the minimum Euclidian distance between the received signal and candidate constellation points, the number of UEs multiplexed at a common RE is determined. Each RE then acts as a voter, who can vote for the activeness of a UE. Several voting schemes are proposed and further enhancement is also designed. Simulations show that by collecting enough number of votes, the proposed UE detection methods can reach a satisfactory detection performance in UL grant-free SCMA transmission. It is also confirmed via simulations that after a precise active UE list is built, the computation complexity of the MPA decoder is reduced and the accuracy of data recovery is improved.

The rest of the thesis is structured as follows. Chapter 2 introduces the system model. Chapter 3 presents fundamental schemes for UE detection. Chapter 4 proposes three voting-based UE detection schemes. Chapter 5 presents the simulation results, including comparisons among various channel fadings, different UE detection schemes, and different number of voters. Finally, Chapter 6 concludes the thesis.
Chapter 2

System Model

This chapter will present the system model of SCMA, which includes the SCMA transmitter in Section 2.1, the channel model in Section 2.2, the SCMA receiver in Section 2.3, and the problem formulation in Section 2.4.

An example of the overall block diagram is shown in Figure 2.1, in which the data stream from each of six user equipments (UEs) is turbo-encoded, interleaved, and then SCMA-encoded before sending it to the channel. At the receiver, a message passing algorithm (MPA) is used to decode the incoming noisy data stream, after which de-interleaving and turbo-decoding operations are subsequently performed.

Figure 2.1: Block diagram of an SMCA system
2.1 SCMA Transmitter

In principle, an SCMA transmitter maps the information bits from multiple UEs to higher dimensional codewords with sparse non-zero components through a pre-specified multi-dimensional constellation. The design of the multi-dimensional constellation includes two steps: i) designing a multi-dimensional mother constellation (MC) and ii) generating the UE-specific codebooks based on the MC.

Specifically, consider an SCMA system with $J$ user equipments (UEs) and $K$ resource elements (REs) in an uplink grant-free scenario. An MC of size $J \times K$ is then formed, in which each UE transmits non-zero complex signals at exactly $N$ REs with $N < K$; hence, $J \leq \binom{K}{N}$. Then, $J$ codebooks, each of which maps $\log_2(M)$ information bits to a $K$-dimensional codeword with $N$ non-zero components, are generated. Afterwards, the $J$ sparse codewords are transmitted simultaneous and hence multiplexed in their transmissions as shown in Figure 2.2. The sparsity of the MC is designed to ensure that the recovery of the UE information from the received multiplexed signal can be done with an acceptable decoding quality. As an example, with $J = 6$, $K = 4$ and $N = 2$, Figure 2.2 illustrates a $6 \times 4$ MC, based on which six codebooks are generated such that only two of
the four codeword components are non-zero.

The MC of an SCMA system can be illustrated by a factor graph as shown in Figure 2.3. The variable nodes (VNs) corresponds to the transmitted data from each UE. The function nodes (FNs) represent REs. The number of non-zero components $N$ in a codeword is thus equal to the number of REs, over which the corresponding UE is allowed to spread its data. Let $d_f$ be the average number of UEs (often referred to as its degree of freedom) that are connected to a single RE. Then under $J = \binom{K}{N}$, we have

$$d_f = \frac{JN}{K} = \frac{\binom{K}{N}}{K} N = \binom{K}{N} \frac{N}{K}.$$

2.2 Channel Model

The channel model we consider is the fast fading channel, in which the channel gains vary considerably among consecutive codeword transmissions, while implicit intracodeword pilots are added to presumably attain a perfect estimation of channel state information (CSI).

Mathematically, the $K \times 1$ received vector can be expressed as

$$y = \sum_{j=1}^{J} \mathbb{H}_j s_j + n \quad (2.1)$$

where $\mathbb{H}_j = \text{diag}(h_{1,j}, \ldots, h_{K,j})$ is the $K \times K$ CSI matrix corresponding to the $j$th UE; $s_j$ is the $K \times 1$ symbol vector of the $j$th UE; and $n \sim \mathcal{CN}(0, \sigma^2 \mathbb{I})$ is the $K \times 1$ noise vector. The channel gains from each UE to all of its connected REs are assumed identical,
while the channel gains from different UEs to a common RE can vary. We thus have 
\[ h_{1,j} = \cdots = h_{K,j} = h_j, \]
based on which (2.1) is simplified to:
\[ y = \sum_{j=1}^{J} h_j s_j + n = \mathbb{S}\mathbb{H}\mathbf{1} + \mathbf{n}, \tag{2.2} \]
where \( \mathbb{S} = [s_1 \cdots s_J] \) is the \( K \times J \) aggregated transmitted symbol matrix; \( \mathbb{H} = \text{diag}(h_1, \ldots, h_{J}) \) is the \( J \times J \) aggregated channel matrix; and \( \mathbf{1} \) denotes the all-one vector of proper size.

The symbol vector \( s_j \) (i.e., the codeword sent by the \( j \)th UE) can be decomposed into 
\[ s_j = \mathbb{C}_j \mathbf{x}_j, \tag{2.3} \]
where \( \mathbb{C}_j \) is the \( K \times M \) spreading signature matrix of the \( j \)th UE, and \( \mathbf{x}_j = [x_{1,j} \cdots x_{M,j}]^T \) is the \( M \times 1 \) vector that satisfies each \( x_{m,j} \in \{0,1\} \) and \( \sum_{m=1}^{M} x_{m,j} = 1 \). As an example, based on the mother constellation in Figure 2.3 and with QPSK modulation (i.e., \( M = 4 \)), \( \{\mathbb{C}_j\}_{j=1}^{J} \) can be given by:
\[
\mathbb{C}_1 = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 1+i & -1+i & -1-i & 1-i \\ 0 & 0 & 0 & 0 \\ 1+i & -1+i & -1-i & 1-i \end{bmatrix}, \quad \mathbb{C}_2 = \begin{bmatrix} 1+i & -1+i & -1-i & 1-i \\ 0 & 0 & 0 & 0 \\ 1+i & -1+i & -1-i & 1-i \\ 0 & 0 & 0 & 0 \end{bmatrix},
\]
\[
\mathbb{C}_3 = \begin{bmatrix} 1+i & -1+i & -1-i & 1-i \\ 0 & 0 & 0 & 0 \\ 1+i & -1+i & -1-i & 1-i \\ 0 & 0 & 0 & 0 \end{bmatrix}, \quad \mathbb{C}_4 = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 1+i & -1+i & -1-i & 1-i \\ 0 & 0 & 0 & 0 \\ 1+i & -1+i & -1-i & 1-i \end{bmatrix},
\]
\[
\mathbb{C}_5 = \begin{bmatrix} 1+i & -1+i & -1-i & 1-i \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 1+i & -1+i & -1-i & 1-i \end{bmatrix}, \quad \mathbb{C}_6 = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 1+i & -1+i & -1-i & 1-i \\ 1+i & -1+i & -1-i & 1-i \\ 0 & 0 & 0 & 0 \end{bmatrix}.
\]
It can be seen from the decomposition in (2.3) that the \(\log_2(M)\) input bits decide the location of the non-zero component in vector \(x_j\). For example, when the first UE transmits bit stream \((0, 0)\), we have \(x_1 = [1 \ 0 \ 0 \ 0]^T\), which, according to (2.3), implies

\[
\begin{bmatrix}
    s_{1,1} \\
    s_{2,1} \\
    s_{3,1} \\
    s_{4,1}
\end{bmatrix} = \begin{bmatrix}
    0 \\
    1 + i \\
    0 \\
    1 + i
\end{bmatrix}.
\]

In order to facilitate the formulation of the factor graph, an \(K \times 1\) indicator vector \(f_j = [f_{1,j} \ \cdots \ f_{K,j}]^T\) is introduced, where its element \(f_{k,j}\) is given by

\[
f_{k,j} = \begin{cases} 
0, & s_{k,j} = 0 \\
1, & s_{k,j} \neq 0
\end{cases} \quad \text{for } k = 1, \ldots, K, j = 1, \ldots, J.
\]

As such, the positions of 1’s in the indicator vector \(f_j\) indicate the positions at which the \(j\)th UE spreads its data. The \(K \times J\) indicator matrix is thus given by \(F = [f_1 \ \cdots \ f_J]\), in which a 1’s corresponds to a non-zero element in codeword matrix \(S\). By following the same example in Figure 2.3, the indicator matrix \(F\) is equal to

\[
F = \begin{bmatrix}
    0 & 1 & 1 & 0 & 1 & 0 \\
    1 & 0 & 1 & 0 & 0 & 1 \\
    0 & 1 & 0 & 1 & 0 & 1 \\
    1 & 0 & 0 & 1 & 1 & 0
\end{bmatrix}.
\]  

(2.4)

By aggregating \(X = [x_1 \ \cdots \ x_J]\), the MAP detection at the receiver gives the optimal estimate \(\hat{X}\) that maximizes the \textit{a posteriori} probability:

\[
\hat{X} = \arg \max_X \Pr(X|y).
\]  

(2.5)

The complexity of the MAP detector, however, increases exponentially with respect to the number of UEs. Thus, in this thesis, a suboptimal message passing algorithm (MPA) is adopted instead.
2.3 SCMA Receiver

An SCMA receiver for uplink grant-free transmissions can be structured as shown in Figure 2.4. Upon the reception of the signals from channels, the MPA decoder outputs the log-likelihood ratios (LLRs) of the coded bits according to the \emph{a priori} probabilities provided by the constellation probability calculator. Then, the extrinsic portion of the newly updated LLRs will be passed to the constellation probability calculator to update the \emph{a priori} probabilities used for the next MPA iteration. At the end of the MPA iterations, the LLRs will be de-interleaved and turbo-decoded in order to recover the data streams.

2.3.1 Message Passing Algorithm

The message passing algorithm (MPA) is an iterative decoding algorithm that operates over the factor graph of the SCMA. With the SCMA sparsity property, computational complexity is significantly reduced when being compared with the optimal exhaustive decoder in (2.5). By treating the multiuser detection problem as a probabilistic inference one, probabilistic messages are iteratively exchanged along the edges between FNs and VNs over the factor graph, and the values of these messages are updated in every iteration. In order to compute or update these messages, the Euclidian distance between the received vector and constellation candidates are obtained first. Detail is given below.
Minimum Euclidian Distance

As previously mentioned, a bit stream from each UE is mapped to a specific symbol. Then, the symbols from \( J \) UEs are multiplexed and sent through the noisy channels.

Recall that the codewords multiplexed at each RE are not necessarily orthogonal. In order to analyze these non-orthogonal signals, we first obtain all constellation candidate vectors \( \mathbf{c} \)'s according to

\[
\mathbf{c} = \sum_{j=1}^{J} h_j \mathbf{s}_j = \sum_{j=1}^{J} h_j \mathbf{C}_j \mathbf{x}_j \quad (2.6)
\]

over all possible \( \mathbf{x}_j \) with \( x_{k,j} \in \{0, 1\} \) and \( \sum_{k=1}^{K} x_{k,j} = 1 \). Let the set of all such \( \mathbf{c} \)'s be denoted by \( \mathcal{C} \). Upon the reception of \( \mathbf{y} = [y_1 \cdots y_K]^T \) defined in (2.1), we calculate the minimum Euclidean distance for each RE via

\[
d_{\min}^{k} = \min_{\mathbf{c} \in \mathcal{C}} \| \mathbf{y}_k - \mathbf{c}_k \|. \quad (2.7)
\]

If \( d_{\min}^{k} \) is small, then the candidate \( \mathbf{c} \) that achieves it should be the transmitted codeword with high probability. The iteration procedure of the MPA can thus be applied by further exploiting the symbol probabilities based on these minimum Euclidean distances and by taking advantage of the SCMA structure.

**Iteration Procedure**

Let \( I_{r_k \rightarrow u_j}(\mathbf{s}_j) \) and \( Q_{u_j \rightarrow r_k}(\mathbf{s}_j) \) be respectively the messages (i.e., probabilities) exchanged between the \( k \)th RE and the \( j \)th UE at the \( t \)th iteration, given that \( \mathbf{s}_j = \mathbf{C}_j \mathbf{x}_j \) was transmitted by the \( j \)th UE. Notably, there are possibly \( M \mathbf{x}_j \)'s to be transmitted. For notational convenience, we let the set of these possible \( \mathbf{x}_j \)'s be denoted by \( \mathcal{X} \). Then, by denoting the sets of UEs and REs that connect to the \( k \)th RE and the \( j \)th UE by \( \xi_k \) and \( \zeta_j \), respectively, the two messages, according to the MPA, are respectively given by

\[
I_{r_k \rightarrow u_j}(\mathbf{s}_j) = \sum_{\{s_{\ell'}\} \in \mathcal{X}_k \setminus \{j\}} \left\{ \frac{1}{\sqrt{2\pi \sigma}} \exp \left( -\frac{\| y_k - \sum_{m \in \xi_k} h_m s_{k,m} \|^2}{2\sigma^2} \right) \right\} \times \prod_{\ell \in \mathcal{X}_k \setminus \{j\}} Q_{u_{\ell} \rightarrow r_k}(\mathbf{s}_{\ell}) \quad (2.8)
\]

and

\[
Q_{u_j \rightarrow r_k}(\mathbf{s}_j) = \prod_{m \in \xi_j \setminus \{k\}} I_{r_m \rightarrow u_j}(\mathbf{s}_j) \quad (2.9)
\]
for every $s_j = C_j x_j$ with $x_j \in \mathcal{X}$, where $\{s_{e'}\}_{e' \in \mathcal{E}_k \setminus \{j\}}$ means that the summations include all possible combinations of $\{s_{e'} = C_{e'} x_{e'}\}_{e' \in \mathcal{E}_k \setminus \{j\}}$ with each $x_{e'} \in \mathcal{X}$. As an example from Figure 2.3, we have $\xi_1 = \{2, 3, 5\}$ and $\zeta_1 = \{2, 4\}$; hence,

\[
I_{r_1 \rightarrow u_2}^{(t)}(s_2) = \sum_{s_3 = C_3 x_3} \sum_{x_3 \in \mathcal{X}} \sum_{x_5 \in \mathcal{X}} \left\{ \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2\sigma^2} \left\| y_{1-h_1 s_1,2-h_3 s_1,3-h_5 s_1,5} \right\|^2} Q_{u_3 \rightarrow r_1}^{(t-1)}(s_3) Q_{u_5 \rightarrow r_1}^{(t-1)}(s_5) \right\}
\]

\[
I_{r_1 \rightarrow u_3}^{(t)}(s_3) = \sum_{s_2 = C_2 x_2} \sum_{x_2 \in \mathcal{X}} \sum_{x_5 \in \mathcal{X}} \left\{ \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2\sigma^2} \left\| y_{1-h_1 s_1,2-h_3 s_1,3-h_5 s_1,5} \right\|^2} Q_{u_2 \rightarrow r_1}^{(t-1)}(s_2) Q_{u_5 \rightarrow r_1}^{(t-1)}(s_5) \right\}
\]

\[
I_{r_1 \rightarrow u_5}^{(t)}(s_5) = \sum_{s_2 = C_2 x_2} \sum_{s_3 = C_3 x_3} \sum_{x_3 \in \mathcal{X}} \sum_{x_5 \in \mathcal{X}} \left\{ \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2\sigma^2} \left\| y_{1-h_1 s_1,2-h_3 s_1,3-h_5 s_1,5} \right\|^2} Q_{u_2 \rightarrow r_1}^{(t-1)}(s_2) Q_{u_3 \rightarrow r_1}^{(t-1)}(s_3) \right\}
\]

and

\[
Q_{u_1 \rightarrow r_2}^{(t)}(s_1) = I_{r_2 \rightarrow u_1}^{(t)}(s_1) \quad \text{and} \quad Q_{u_1 \rightarrow r_1}^{(t)}(s_1) = I_{r_2 \rightarrow u_1}^{(t)}(s_1).
\]

It is assumed that each UE transmits an independent and identically distributed (i.i.d.) bit stream of length $\log_2(M)$, where the probability of each bit being 0 or 1 is identical. The initial value of symbol’s probability at the $j$th UE is given by

\[
Q_{u_j \rightarrow r_j}^{(0)}(s_j) = \left( \frac{1}{2} \right)^{\log_2(M)} = \frac{1}{M}.
\]

After the last iteration, the final estimate of the transmitted symbol at the $j$th UE is made based on

\[
Q_{u_j}(s_j) = \prod_{m \in \zeta_j} I_{r_m \rightarrow u_j}^{(t)}(s_j).
\]

We briefly elaborate on the recursions above. According to (2.8), at the $t$th iteration, the FN messages are updated by using the VN messages obtained at the $(t-1)$th iteration. Yet, if the FN message associated with $s_j$ is updated, only the VN messages from the UEs that share the same RE with the $j$th UE are included. Note that in order to substantialize the information passed from the other UEs, the VN message from the $j$th UE is excluded.

Similarly, according to (2.9), the VN messages are updated by using the FN messages just obtained at the $t$th iteration. Only the other FN messages from the REs that share the same UE with the $k$th RE are used, and the FN message from the $k$th RE is excluded. For this reason, these messages are often referred to as the extrinsic information.
Extrinsic Information

In order to have a robust estimate on the transmitted symbol, the information messages are updated via the recursions described previously. We now provide further remarks on its update procedure.

Consider an SCMA system with $J$ UEs (which are regarded as VNs on the factor graph), where each UE spreads its data onto $N$ REs (which are regarded as FNs on the factor graph).

Each FN passes the update messages obtained from extrinsic information to its neighboring VNs. For example, when updating $I^{(t)}_{r_{1} \rightarrow u_{2}}(s_{2})$, the informational messages from VE#3 (i.e., $Q^{(t-1)}_{u_{3} \rightarrow r_{1}}(s_{3})$) and VE#5 (i.e., $Q^{(t-1)}_{u_{5} \rightarrow r_{1}}(s_{5})$) are extrinsic. In order to avoid the messages (obtained from neighboring VEs) intervening each other, these extrinsic information messages are stored before they are separately applied in the update of (2.8). As the extrinsic information messages that suffer from bad channels only contribute partially to each update, the overall performance will not degrade considerably as long as the reliable messages can compensate for the degradation due to unreliable messages. As such, the estimate remains robust.

Similarly, each VN passes update obtained from extrinsic information to its neighboring FNs according to (2.9) and the extrinsic information messages $\{I^{(t)}_{r_{k} \rightarrow u_{j}}(s)\}$ are stored before they are separately applied in the update of (2.9).

At the end of the recursions, all information messages are multiplied altogether as shown in (2.15). In order to ease the burden of normalization operation that forces the satisfaction of

$$\sum_{s_{j} = C_{j}, x_{j} : x_{j} \in \mathcal{X}} Q_{u_{j}}(s_{j}) = 1,$$

the probability of each bit is converted to log-likelihood ratio (LLR) at the end of the recursions. For an SCMA decoder, the a posteriori LLR of coded bit $b_{i}^{j}$ conditioned on received value $y_{k}$, where $b_{i}^{j}$ denotes the $i$th bit of the $j$th UE for $1 \leq i \leq \log_{2}(M)$, is given by

$$L_{k}(b_{i}^{j}) = \log \left\{ \frac{\Pr(b_{i}^{j} = 1|y_{k})}{\Pr(b_{i}^{j} = 0|y_{k})} \right\} . \quad (2.16)$$
By Bayes’ law, the output of an MPA decoder can be expressed as

\[ L_k(b^j) = \log \left\{ \frac{p(y_k | b^j = 1)}{p(y_k | b^j = 0)} \right\} + \log \left\{ \frac{p(b^j = 1)}{p(b^j = 0)} \right\} \]

\[ = L_k^c(b^j) + L^a(b^j), \] (2.17)

where by denoting the set of \( x \)'s whose corresponding bit label at position \( i \) is \( b \) by \( X_i^{(b)} \), we have

\[ L_k^c(b^j) = \log \left\{ \sum_{s_j = C_j, x_j \in X_i^{(1)}} \prod_{m \in \zeta_j \setminus \{k\}} I_{r_m \rightarrow u_j}(s_j) \right\} \]

\[ \sum_{s_j = C_j, x_j \in X_i^{(0)}} \prod_{m \in \zeta_j \setminus \{k\}} I_{r_m \rightarrow u_j}(s_j) \] (2.19)

and

\[ L^a_i(b^j) = \log \left\{ \frac{\sum_{s_j = C_j, x_j \in X_i^{(1)}} Q_{u_j}(s_j)}{\sum_{s_j = C_j, x_j \in X_i^{(0)}} Q_{u_j}(s_j)} \right\}. \] (2.20)

### 2.4 Problem Formulation

In practice, the number of active UEs varies, depending on the corresponding traffic loads, and some UEs may be idle. As such, the receiver of an uplink grant-free SCMA system may need to decode data from UEs without the knowledge of whether they are active or not.

A solution is to include \( x = [0 \ 0 \ \cdots \ 0]^T \) into the set of all possible transmissions \( X \) during the decoding process, which not only increases the decoding complexity but limits the performance. Alternatively, one can learn whether UEs are active or not through the first few transmissions within a resource block (RB), based on which the receiver can focus on the decoding of the data from active UEs by ignoring entirely the idle UEs. Notably, it is operationally reasonable from 5G standards that a UE is either active or idle in all transmissions within a RB, which justifies the possibility of UE detection in terms of first few transmissions.

Along this idea, a \( J \times J \) diagonal matrix \( U = \text{diag}(u_1, u_2, \ldots, u_J) \) is employed, where \( u_j = 1 \) (respectively, 0) indicates that the \( j \)th UE is active (respectively, idle). Together with the indicator matrix \( F \) in Section 2.2, a new factor graph can be formed based on

\[ W = FU. \] (2.21)
Figure 2.5: New factor graph corresponding to $\mathbf{W}$ in (2.22).

Continue from the example in Figure 2.3. If only UE 1, UE 2, UE 4 and UE 6 are active in an RB, then the status matrix $\mathbf{U}$ is $\text{diag}(1, 1, 0, 1, 0, 1)$. We can thus compute $\mathbf{W}$ as

$$\mathbf{W} = \begin{bmatrix} 0 & 1 & 1 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 & 0 & 1 \\ 0 & 1 & 0 & 1 & 0 & 1 \\ 1 & 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 & 1 \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 1 \\ 1 & 0 & 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 \end{bmatrix}.$$  \hspace{1cm} (2.22)

As a result, in comparison with the original factor graph in Figure 2.3, a new factor graph is obtained as illustrated in Figure 2.5. Since the decoding complexity is proportional to $M^{d_f}$, the decoding complexity is reduced once the active UEs can be identified. Therefore, a precise UE detection is essential for the decoding efficiency as well as the data retrieval performance. In the next chapter, we shall propose a UE detection scheme for the SCMA system.
Chapter 3

Schemes for UE Detections

This chapter elaborates two detection schemes that can be used for the detection of active UEs. They are the generalized likelihood ratio test (GLRT) and the joint message passing algorithm (JMPA). These two schemes will be respectively introduced in Sections 3.1 and 3.2.

3.1 Generalized Likelihood Ratio Test (GLRT)

The received constellation, based on which the data detection is performed at a RE, apparently depends on the number of multiplexed non-orthogonal signals at the same RE. When the number of active UEs decreases, so will the number of candidate constellation points. As an example, if three UEs that employ QPSK modulation are active at a RE, the number of candidate constellation points is equal to 64. If, however, only two UEs are active, then the number of constellation points is reduced down to 16. These two constellations can be regarded as two different modulations. Accordingly, the problem of finding the correct constellation is equivalent to a modulation classification problem.

A commonly used approach for modulation classification is the generalized likelihood ratio test (GLRT). The notion behind GLRT can be described as follows. Assume that only two modulation schemes are considered, which according to (2.6), result in two candidate codeword sets $C_1$ and $C_2$ for constellation vector $c$. Under the assumption that
the two candidate codeword sets have the same cardinality, i.e., \(|C_1| = |C_2|\), a GLRT classification rule over the \(k\)th RE is given by:

\[
J_k(C_1) \triangleq \min_{c_k \in C_1} \|y_k - c_k\|^2 \overset{C_2}{\geq} \min_{c_k \in C_2} \|y_k - c_k\|^2 \triangleq J_k(C_2),
\]

where \(y_k\) is the received scaler at the \(k\)th RE and \(c_k\) is the \(k\)th component of codeword vector \(c\) defined through (2.6). Note that (3.1) is a consequence of the maximum a posteriori (MAP) decision rule.

When \(|C_1| \neq |C_2|\), the a priori probability of the constellation point in \(C_1\) (which equals \(1/|C_1|\)) is no longer equal to that of the constellation point in \(C_2\), which is \(1/|C_2|\). The MAP decision rule then compensates for the unequal prior probability by a bias term, yielding that:

\[
J_k(C_1) + 2\sigma^2 \log(|C_1|) \overset{C_2}{\geq} J_k(C_2) + 2\sigma^2 \log(|C_2|).
\]

The above GLRT rule indicates that a constellation with more constellation points tends to have a smaller \(J_k(\cdot)\) value, and hence should be compensated by adding a larger bias term in proportion to the logarithm of the number of constellation points.

Continue from the example in Figure 2.2 with \(d_f = 3\). Without the knowledge of each UE status, the codeword constellation may have \(2^3\) shapes, referring to as \(C_1, C_2, \ldots, C_8\). We propose to compute their respective \(J_k(C_m) + 2\sigma^2 \log(|C_m|)\) values, among which the smallest one is regarded as the most possible combination of the statuses of \(J\) UEs.

In order to make a reliable decision, voting based on the decisions from a number of REs will be carried out. In other words, if a UE is regarded as active based on the decision from a RE, it obtains one vote for its activeness. The total number of votes will then be examined via a threshold-type function to finalize the decision. Detail will be given in the next chapter.

### 3.2 Joint Message Passing Algorithm (JMPA)

Another detection scheme that can be used for the determination of the status of each UE is the joint message passing algorithm (JMPA). The idea is to detect the UE status jointly with the MPA decoding.
Figure 3.1: Extended constellation for QPSK under JMPA

Observe that if a particular UE is inactive, it is equivalent to virtually sending the all-zero codeword \( \mathbf{0} \). In other words, such case can be equivalently regarded as having an extra constellation point, called the zero constellation point. Consequently, the number of constellation points will become \( M + 1 \), instead of \( M \). For example, under the JMPA scheme, the QPSK constellation is extended as shown in Figure 3.1, where an additional \((0, 0)\) constellation point is added.

Accordingly, the JMPA scheme is simply an MPA scheme applied over an extended constellation \( \mathcal{C}^e = \mathcal{C} \cup \{\mathbf{0}\} \), given that \( \mathcal{C} \) is the original codeword constellation set. The decoding procedure follows the same recursions in Section 2.3. However, the prior probability for each constellation point in the extended constellation is no longer assumed uniform since the probability of a UE being active is assumed to be equal to that of its being inactive. Thus, the initial probability of the all-zero constellation point is \( 1/2 \), and that of the remaining constellation point is \( 1/(2 \cdot |\mathcal{C}|) \). At the end of JMPA iterations, only when a UE is declared active, the bit LLRs of the UE are calculated and the data are retrieved.
Chapter 4

Voting Based UE Detection Methods

In this Chapter, several UE detection schemes that we proposed are introduced. Specifically, Section 4.1 presents the system formulation for UE detection. Section 4.2 introduces how votes are collected and used in the proposed UE detection schemes.

4.1 System Formulation for UE Detection

In an UL grant-free multiple-access scenario, resources are pre-arranged for UEs, and data transmissions are performed without a request/grant procedure. Since UEs may not transmit their data at a pre-arranged resource, the receiver must either incorporate such possibility in data detection (such as JMPA) or introduce an additional UE detection step as illustrated in Figure 4.1. The latter approach then requires a UE detection scheme.

Assume that $P$ UEs are arranged to transmit data at a resource, for which a potential UE list \{UE 1, \ldots, UE $P$\} is built. Suppose that each UE will be either active or idle during an entire RB. Voting on the status of each UE can thus be carried out based on those receptions within a RB. The voting result establishes an estimate of the active UE list \{UE 1, \ldots, UE $A$\} with $A \leq P$. This active UE list is subsequently used by the MPA decoder to update the transmission status matrix $\mathbf{U}$ according to Section 2.4, and the factor graph, over which the MPA is operated, is thus formed from $\mathcal{W} = \mathbf{F} \mathbf{U}$. As a result, the algorithmic complexity of the MPA decoder is reduced, and the error rate of data
4.2 Voting Strategies on Active UEs

Following the structure in Figure 2.2, we demonstrate the framework of the voting process in Figure 4.2. In this framework, each RE votes for the activeness of a UE via the modified GLRT method stated in Section 3.1. Particularly, the declared constellation at each RE indicates a certain combination of active UE transmissions. If a UE is identified as active, then it gets one vote from the RE. After all REs in an SCMA codeword carry their votes, the voting process proceeds to the next codeword.

In an SCMA transmission block that consists of $N_{cw}$ codewords, an active UE gets at most $N_{vote} = N_{cw} \times N$ votes, where $N$ is the number of REs that a UE spreads its data onto in a codeword. The voting process continues until the last voter has carried its vote. After all the REs have voted, the voting result is recorded. Through analyzing the total number of votes by threshold-type functions, the transmission status of each UE is determined.

Three voting threshold functions are proposed in this thesis, including $i$) hard decision (cf. Section 4.2.1), $ii$) two-phase hard decision (cf. Section 4.2.2), and $iii$) two-phase hard decision based on vote difference (cf. Section 4.2.3).
4.2.1 Hard Decision

To analyze the voting result with the hard decision scheme, a voting threshold is set. If the number of votes that a UE receives is larger than the threshold, then the UE is declared as active; otherwise, it is marked as idle. When a tie occurs, an arbitrary decision is given. Since the probability of a UE being active is assumed to be equal to that of its being inactive, we set the threshold as

\[ N_{\text{thres}} = \frac{1}{2} N_{\text{vote}}. \] (4.1)

The transmission status matrix \( U = \text{diag}(u_1, \ldots, u_J) \) is thus defined as follows:

\[ u_j = \begin{cases} 
1, & N_{\text{final}}^j \geq N_{\text{thres}}; \\
0, & N_{\text{final}}^j < N_{\text{thres}}, 
\end{cases} \] (4.2)

where \( N_{\text{final}}^j \) is the number of votes the \( j \)th UE ultimately receives.

The detection performance of the hard decision scheme is acceptably good only when \( N_{\text{vote}} \) is sufficiently large, which results in a proportionally large computational complexity as well as processing delay. In order to alleviate the requirement of computational complexity and processing delay for an acceptable performance, we continue to propose the two-phase hard decision scheme.

4.2.2 Two-phase Hard Decision

In this scheme, the voters are equally divided into two groups, which are used for two operational phases, respectively.
In the first phase, votes from voters in the first group are collected; but a different threshold function from (4.1) is employed as follows:

\[
  u_j = \begin{cases} 
  1, & N_{\text{phase1}}^j > N_{\text{high}}; \\
  0, & N_{\text{phase1}}^j < N_{\text{low}}; \\
  \text{undecided, otherwise,} & 
  \end{cases}
\]  

(4.3)

where \( N_{\text{phase1}}^j \) is the number of votes the \( j \)th UE receives in the first phase, and

\[
  N_{\text{high}} = \frac{3}{4} \left( \frac{N_{\text{vote}}}{2} \right) \quad \text{and} \quad N_{\text{low}} = \frac{1}{4} \left( \frac{N_{\text{vote}}}{2} \right).
\]  

(4.4)

It is obvious from (4.3) that a UE is declared active in the first phase only when it receives three fourths of the total votes, in which case we are more confident in the declaration of its activeness. We can likewise interpret those UEs that are declared inactive in the first phase. For those UEs whose number of votes is between \( N_{\text{high}} \) and \( N_{\text{low}} \), their status is set to be “undecided” and their votes are retained for use in the second phase.

In the second phase, we again apply the modified GLRT method to determine the most probable constellation combination. However, since the statuses of some UEs are already declared, the number of candidate constellations is accordingly decreased. For example, when \( d_f = 3 \), there are \( 2^3 \) candidate constellations that should be considered by the modified GLRT. If one of the three UEs that are connected to this RE is declared in the first phase, then the number of candidate constellations is reduced to \( 2^2 \). We again obtain the final vote number \( N_{\text{final}}^j \) for each UE with undecided status, and apply (4.1) for the final decision of the statuses of these UEs.

With the two-phase hard decision scheme, the performance of UE detection can be improved. Nevertheless, its thresholds are fixed and cannot adapt to the fluctuation of signal-to-noise ratios (SNRs). In particular, these thresholds may need to be adjusted at low SNR. We thus propose to amend this via thresholding the vote difference.
4.2.3 Two-phase Hard Decision based on Vote Difference

In this UE detection scheme, voters are evenly divided into two groups for use respectively in two operational phases, as similar to the two-phase hard decision scheme in the previous subsection. The second phase of this scheme, however, adopts a different threshold function.

Due to the extra information that some UE statuses are declared with confidence, the probabilities of candidate constellation combinations in the second operational phase may not be uniform. Therefore, the final decision based on the threshold specified in (4.1) may be far from optimal. Specifically, subject to the premise that the declarations in the first phase are all correctly made, if a UE with undecided status in the first phase is truly active at the transmitter, it should get more votes in the second phase because the modified GLRT decision in the second phase is more accurate than that in the first phase. On the other hand, an inactive UE should receive lesser votes in the second phase than in the first phase if the declarations in the first phase are all correct. This observation leads to the modification that the decision on the status of a UE should be made based on the vote difference between the first and the second phases. We thus propose:

\[ u_j = \begin{cases} 
1, & N_{\text{diff}}^j \geq 0; \\
0, & N_{\text{diff}}^j < 0, 
\end{cases} \]  

(4.5)

where \( N_{\text{diff}}^j = N_{\text{phase2}}^j - N_{\text{phase1}}^j \), and \( N_{\text{phase1}}^j \) and \( N_{\text{phase2}}^j \) are the numbers of votes received by the \( j \)th UE in the first and second phases, respectively.

In comparison with the fixed thresholds adopted in the two-phase hard decision scheme in the previous subsection, the notion of vote difference can adapt better to different SNRs. This is particularly important at low SNR as both the two-phase hard decision and the vote-difference-based two-phase hard decision perform well at high SNRs.

From the hard decision voting scheme based on vote difference in this subsection, flexibility on the decision thresholds is indeed a crucial factor, which should be a function of the \textit{a posteriori} probability of an UE being active and inactive. A further improvement along this direction can be potentially rendered via an enhanced JMPA detector.
4.2.4 JMPA Enhancement of Hard Decision Voting Schemes

In the previous subsections, the statuses of UEs are decided by threshold-type functions of votes. However, when the numbers of votes turn out to be mostly around the threshold, the resultant majority decision may not provide an acceptable performance.

In order to alleviate this problem, a JMPA enhancement that can be applied to both hard decision voting scheme (Subsection 4.2.1) and two-phase hard decision voting scheme (Subsection 4.2.2) is further proposed. As shown in Figure 4.3, at the end of the two schemes, the statuses of those UEs, whose number of final votes $N_{\text{final}}$ is within $\frac{7}{8} \times N_{\text{thres}}$ and $\frac{9}{8} \times N_{\text{thres}}$ with $N_{\text{thres}} = N_{\text{vote}}/2$, are redefined as “uncertain.” We then apply the JMPA method stated in Section 3.2 to these uncertain UEs. By adding an extended constellation point that reflects the state of an inactive UE sending the all-zero codeword $0$ with prior probability $\frac{1}{2}$, and letting the probability of sending all other codewords in $\mathcal{C}$ be $\frac{1}{2^{k-1}}$, where $\mathcal{C}$ is the original codeword set without codeword $0$, the statuses of these uncertain UEs will be decided by the JMPA and an adjusted active UE list is accordingly generated.

Through the JMPA enhancement, the performance of the UE detection can be im-
proved within a few JMPA iterations. The enhancement adapt the UE decision to the SNR fluctuation. Once the statuses of UEs are precisely detected, the MPA decoder can then effectively retrieve the data.
Chapter 5

Experimental Results

In this chapter, simulation results for the proposed UE detection schemes and the MPA decoders are given in Sections 5.1 and 5.2, respectively. In all simulations, an SCMA codeword structured with $J = 6$ UEs and $K = 4$ REs is considered as illustrated in Figure 2.3. In an SCMA transmission block, the number of information bits that are turbo-encoded with rate $1/3$ at each UE is $N_{IB} = 80$, which results in $N_{CB} = 240$ codebits per UE. With QPSK modulation (i.e., $N_B = 2$), $N_{CW} = N_{CB}/N_B = 120$ codewords are accordingly transmitted in an SCMA transmission block. It is also assumed that all UEs experience the same SNR, and perfect CSI estimation can be achieved.

5.1 Examination of UE Detection

We examine the proposed UE detection schemes in this section. Specifically, the performance impact due to various channel fadings, different UE detection schemes and different numbers of voters are presented in Sections 5.1.1, 5.1.2 and 5.1.3, respectively. Then, Section 5.1.4 summarizes the probabilities of mis-detection (where an active UE were declared inactive) and false alarm (where an inactive UE were treated active, which causes unnecessary decoding effort for data retrieval) for the first three UE detection
schemes introduced in Section 4.2.\textsuperscript{1} Finally, Section 5.1.5 presents the performance improvement of the enhanced UE detection scheme in Section 4.2.4.

In what follows, the UE detection error probability (equivalently, the UE detection error rate), denoted as $\epsilon_{\text{eue}}$, is calculated according to:

$$\epsilon_{\text{eue}} = \frac{N_{\text{eue}}}{N_{\text{scb}} \times J}, \quad (5.1)$$

where $N_{\text{eue}}$ is the total number of erroneous UE detection occurred during a simulation run, and $N_{\text{scb}}$ is the number of SCMA transmission blocks tested in this simulation, each of which contains $N_{\text{CW}}$ codewords.

### 5.1.1 Impact Due to Various Channel Fadings

In this section, we compare the effect of fast fading on UE detection with that of block fading. Different from the fast fading channel model introduced in Section 2.2, the channel gains experienced by $N_{\text{CW}}$ codewords in an SCMA transmission block are all identical under the block fading channel model. Based on the two-phase hard decision scheme in Section 4.2.2 with $N_{\text{vote}} = 80$ (hence, $N_{\text{high}} = \frac{3}{4}(N_{\text{vote}}^2) = 30$ and $N_{\text{low}} = \frac{1}{4}(N_{\text{vote}}^2) = 10$), we obtain the UE detection error probabilities under the two channel models as shown in Figure 5.1.

It can be observed from the figure that the UE detection error probability is significantly better when transmitting over the fast fading channel. This is an anticipated result since the success of voting strategies relies strongly on the diversity of individual votes. In a homogeneous statistical environment such as the block fading channel, all votes suffer from identical fading and hence may unanimously reach erroneous decisions. By contrast, the independent variations of channel gains under the fast fading channel provide additional diversity gain, where the votes that suffer severe fading can be compensated by those that are obtained under mild fading. This indicates that voting strategies are much

\textsuperscript{1}Our definitions of mis-detection and false alarm follow from those in [4]. Note that the authors in [6] define “false alarm” as the situation that an active UE were declared active, and “miss detection” for mistreating inactive UE as active, which are opposite of the definitions in [4].
5.1.2 UE Detection for Different Voting Strategies

We now examine the performances of the first three UE detection schemes proposed in Section 4.2. The results are summarized in Figures 5.2 and 5.3. It can be observed from the two figures that both two-phase UE detection schemes considerably outperform the hard decision UE detection scheme. It indicates that the threshold function applied in the first phase of the two-phase schemes effectively classifies the UE statuses into three groups: active, inactive and undecided, based on which the modified GLRT in the second phase can well identify the statuses of those undecided UEs.

In addition, at low SNRs, active UEs get fewer votes (in comparison with those obtained at high SNRs) and hence the mis-detection probability dominates the UE detection
error rate. As a result, a more flexible threshold function, adopted by the two-phase hard decision based on vote difference, results in a better performance than the two-phase hard decision scheme. Further discussion on mis-detection and false alarm will be given in Section 5.1.4.
Figure 5.3: UE detection error rates of the first three schemes proposed in Section 4.2 under $N_{vote} = 120$
5.1.3 Impact Due to Different Numbers of Votes

In the SCMA system we consider, each UE can at most obtain 240 votes, since in each SCMA codeword, an UE spreads its data to two REs, and there are $N_{CW} = 120$ codewords in an SCMA transmission block. Consequently, a trade-off between the number of voters and the operational complexity of UE detection follows.

Figures 5.4 and 5.5 depict the performances for the two two-phase hard decision schemes, respectivey, with respect to different numbers of voters $N_{\text{vote}}$. As anticipated, a better UE detection performance can be rendered when more voters are involved, but the complexity increases as the number of voters grows. For example, we observe from Figure 5.4 that with $N_{\text{vote}} = 240$, $\epsilon_{\text{ue}}$ achieves $10^{-5}$ when SNR reaches 7 dB; however, with $N_{\text{vote}} = 80$, it requires SNR = 10 dB to achieve the same UE detection error.
Figure 5.5: UE detection error rates for two-phase hard decision scheme based on vote difference under different number of voters $N_{\text{vote}}$.
5.1.4 Mis-detection and False Alarm

The UE detection error rate can be separated into two parts: *mis-detection* and *false alarm* [4]. A mis-detection regards the situation that an active UE is declared as inactive. On the contrary, a false alarm indicates that an inactive UE is identified as active, causing unnecessary decoding burden and interference to those truly active UEs.

Figures 5.6 and 5.7 show the probabilities of mis-detection and false alarm under $N_{\text{vote}} = 80$. It can be observed from the two figures that at low SNRs, mis-detection dominates the UE detection error, implying that active UEs tend not to receive the required numbers of votes to substantiate their activeness; thus, active UEs are apt to be mistaken as idle. As we have expected, the flexibility on thresholds in the scheme of two-phase hard decision with vote difference can alleviate the mis-detection errors, and improves the probability of mis-detection at low SNRs.

At high SNRs, on the contrary, a fixed threshold is sufficient to identify active UEs; hence, false alarm becomes a dominant factor to the UE detection error rate. Note that when false alarm occurs, extra interference in the data decoding that follows will be introduced, resulting in a deteriorated data retrieval error rate. A solution to the extra interference caused by false alarm is the JMPA detector, which will be examined in the next subsection.
Figure 5.6: Probabilities of mis-detection and false alarm for the two-phase hard decision scheme.

Figure 5.7: Probabilities of mis-detection and false alarm for the two-phase hard decision scheme based on vote difference.
We now turn to the JMPA enhancement for UE detection introduced in Section 4.2.4. The enhancement takes advantage of the SCMA iteration structure and re-adjusts those UEs marked as uncertain. Figure 5.8 depicts the improvement on the UE detection error probabilities for the two-phase hard decision scheme under $N_{\text{vote}} = 80$. It indicates that a significant improvement can be obtained, in particular from SNR = 3 to 8 dBs.

We further examine the individual improvements respectively on probabilities of misdetection and false alarm due to JMPA enhancement. It can be observed from Figure 5.9 that the JMPA enhancement improves both probabilities except that the UE detection with the JMPA enhancement has a slightly worse probability of false alarm at SNR smaller than 3 dB. Such a slight deterioration in probability of false alarm, as will be seen in the next section, has negligible impact on the data retrieval by the subsequent MPA decoder.
Figure 5.9: Improvements on probabilities of mis-detection and false alarm for the two-phase hard decision scheme due to JMPA enhancement.
5.2 Simulation Results for MPA Decoders

In this section, simulations results for MPA decoders are presented. Specifically, Section 5.2.1 provides the data recovery performance based on the UE detection from the proposed voting schemes, and Section 5.2.2 further examines the performance variation for non-uniform statistics on UE status.

Before we proceed to present the simulation results, we repeat that after the active UE list is built by the UE detection schemes, the 4-iteration MPA decoder will recover the data transmitted by the active UEs. The block error rate (BLER) will be calculated according to

\[ \text{BLER} = \frac{N_{\text{block}}}{N_{\text{sch}} \times J}, \quad (5.2) \]

where \( N_{\text{block}} \) is the total number of error blocks for \( J \) UEs among \( N_{\text{sch}} \) SCMA transmission blocks.

5.2.1 MPA Decoders based on UE Detection

In this subsection, we examine the data recovery performance based on the active UE list built by the proposed UE detection scheme. For completeness, the performance comparison with the JMPA detector that can be regarded as detecting UE status and recovering UE data simultaneously, as introduced in Section 3.2, will be provided.

Figures 5.10 and 5.11 depict the resulting BLERs respectively for the two-phase hard decision scheme and the two-phase hard decision based on vote difference. It can be observed that at \( \text{BLER} = 10^{-5} \), the combination of UE detection and MPA decoder performs around 4 dB better than the JMPA when \( N_{\text{vote}} \) is set to be its maximum value 240. For completeness, we also provide the UE detection error rates respectively for the two two-phase UE detection schemes that combine with the MPA decoder and for the JMPA in Figure 5.2.1.

Figures 5.10 and 5.11 also indicate that a comparable performance between the UE detection/MPA decoding concatenation and the JMPA can be obtained if \( N_{\text{vote}} \) is reduced to 80. We conclude that the proposed UE detection schemes can help improve effectively
Figure 5.10: BLERs for the two-phase hard decision and for the JMPA with respect to different number of voters.

The performance of the JMPA when one third of the maximum number of voters is used for UE detection.
Figure 5.11: BLERs for the two-phase hard decision based on vote difference and for the JMPA with respect to different number of voters.

Figure 5.12: UE detection error rates for the UE detection/MPA decoding concatenations and for the JMPA when $N_{\text{vote}} = 240$.
5.2.2 Non-uniformly Distributed UE Status

In all previous simulations, the probability of a UE being active is assumed to be equal to that of its being idle. However, the system may encounter heavy traffic loads that boost the probability of UE activeness. On the contrary, low traffic demands may occur occasionally, which induces a low transmission probability from UEs.

In order to evaluate how this transmission probability affects the system performance, simulations are performed and summarized in Figures 5.13 and 5.14. It can be noted from the two figures that both the UE detection error rate and the BLER increase as the transmission probability grows. This is because the interference among UE transmissions is less severe when the transmission probability is reduced. As expected, under a low transmission probability, the data retrieval for active UEs is less likely to be interfered from other UEs’ transmissions once the UE statuses are correctly detected. Also, with less severe mis-detection and false alarm due to a low transmission probability, the MPA decoder has a higher probability of successfully decoding.

A final note in this subsection is that the proposed UE detections can also be used to determine the traffic loads, based on which adjustment for further improvement of system performance may be a future work of practical interest.
Figure 5.13: UE detection errors and BLERs for two-phase hard decision under different transmission probabilities

Figure 5.14: UE detection errors and BLERs for two-phase hard decision based on vote difference under different transmission probabilities
Chapter 6

Conclusion

This thesis proposed three voting-based UE detection strategies and an JMPA enhancement to support massive connectivity in the SCMA UL grant-free scenario. It was shown by simulations that the proposed detection schemes can improve the decoding performance, as well as the computational complexity, of the MPA decoder.

Specifically, over fast fading channels, we proposed a modification of the GLRT to identify the active UEs at each RE. The decisions, treated as votes, are then collected, and threshold functions are proposed to make the final decision on the status of each UE.

Simulation results showed that with sufficient number of voters, both the two-phase hard decision scheme and the two-phase hard decision based on vote difference scheme can achieve a good detection probability of error. When co-worked with the MPA decoder, the resulting decoding performance can outperform the JMPA scheme. We further proposed a JMPA enhancement to the hard decision voting scheme in order to reduce both misdetection and false alarm probabilities. We also perform simulations for different UE active probabilities, and conclude that the proposed UE detection schemes can adapt well to the variations of UE active probabilities, in particular the detection error rate is reduced under a low UE active probability.
Bibliography


