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Neighboring Cell Search Techniques for LTE Systems

Yuan Shen, Student Member, IEEE, Tao Luo, and Moe Z. Win, Fellow, IEEE

Abstract—Long term evolution (LTE) is envisioned to be a key technology for the 4G wireless communication. In LTE systems, each user (UE) detects the surrounding base stations by searching the primary and secondary synchronization channel symbols in the received signal. Searching and tracking neighboring base stations is of great interest for UEs' handover and other applications such as base station cooperation. In this paper, we formulate the problem of neighboring cell search (NCS) for LTE systems and investigate this problem from both theoretical and practical perspectives. In particular, we first derive the sufficient signal metrics for NCS under various channel conditions and develop NCS algorithms based on these metrics. We also implement the algorithms on the simulator to validate its effectiveness.

Index Terms—Neighboring cell search (NCS), long term evolution (LTE), orthogonal frequency-division multiple access (OFDMA), multiuser detection, successive interference cancellation

I. INTRODUCTION

Long term evolution (LTE) is a part of the evolving universal mobile telecommunications system (UMTS) beyond high speed packet access (HSPA) and is envisioned as the key technology for the 4G wireless communication [1]. In LTE systems, cell ID information is carried by both the primary synchronization channel (P-SCH) and secondary synchronization channel (S-SCH) symbols, which are transmitted repeatedly every 5 ms. The LTE standard [1], [2] defines each P-SCH symbol be one of the three length-62 Zadoff-Chu (ZC) sequences, and each S-SCH symbol be composed of two interleaved scrambled length-31 *m*-sequences; both are padded with two zeros at the beginning and in the middle to be of length 64. There are 504 different S-SCH symbols are assigned to different OFDM subcarriers.

While P-SCH symbols are mainly dedicated for synchronization,² S-SCH symbols provides complete information about the cell ID. Thus, neighboring cell search (NCS) refers to detecting the IDs of nearby base stations from the aggregated S-SCH symbols in the received signal. Due to the strong

Tao Luo is with Corporate R&D at Qualcomm Inc., QRC-701C, 5775 Morehouse Drive, San Diego, CA 92121 USA (email: tluo@qualcomm.com).

¹There are two different S-SCH symbols called S-SCH1 and S-SCH2. Without loss of generality, our analysis is based on S-SCH1 in this paper, whereas S-SCH2 can be treated similarly.

²P-SCH symbols can also provide cell group IDs, which are divided into three groups. Due to the large number of cell IDs (504), this group ID information can be neglected for cell identification. Specific issues in synchronization are not addressed in this paper and can be found, for example, in [3]–[5].

sidelobes in the cross-correlation of different S-SCH symbols, interference cancellation is necessary prior to select the peaks of the cross-correlation outputs [6]. The NCS problem appears similar to the multiuser detection (MUD) in uplink CDMA systems [7], [8]. However, this problem is different from MUD in the following ways: 1) the set of neighboring cells is unknown in NCS and the aim is to detect those cells, while users are known in MUD and the aim is to decode the data transmitted by users; 2) power control is absent in transmission in NCS, while power control is enforced in uplink CDMA for MUD; 3) S-SCH symbols are composed of two interleaved scrambled *m*-sequences, which have poor cross-correlation property for some pairs of sequences, while signatures of CDMA systems are pure *m*-sequences that have good cross-correlation property [9].

In this paper, we will investigate the NCS problem for LTE systems from both theoretical and practical perspectives. We consider a semi-synchronous systems where arrivals from different cells are within the cyclic prefix (CP) such that the S-SCH sequences of neighboring cells can be entirely captured in one symbol period [10], [11].³ The results are valid for asynchronous systems, where we need repeated initial synchronization before searching each cell. The main contributions of this paper are as follows:

- We formulate the NCS problem in LTE systems and derive the *sufficient signal metric* (SSM) for multi-cell search in both flat-fading and multipath channels;
- We derive the SSMs that combine multiple observations over time (multiple radio frames) and/or space (multiple antennas);
- We develop a NCS algorithm based on the derived SSMs and interference cancellation, and implement the algorithm on a link level simulator.⁴

Notation: The notation $[\cdot]^{\dagger}$ and $[\cdot]^{*}$ are the Hermitian transpose and the complex conjugate of its argument, respectively. The notation $\langle \mathbf{x}, \mathbf{y} \rangle = \mathbf{x}^{\dagger} \mathbf{y}$ is the inner product of the vectors \mathbf{x} and \mathbf{y} , and operation $\mathbf{x} \otimes \mathbf{y}$ denotes element-wise multiplication of \mathbf{x} and \mathbf{y} . The notation $\Re \mathfrak{e} \{\cdot\}$ is the real part of its argument, $\|\cdot\|$ denotes the Euclidian norm of its argument, and $|\mathcal{N}|$ denotes the cardinality of a finite set \mathcal{N} .

⁴The simulator is developed by Corporate R&D at Qualcomm Incorporate.

Yuan Shen and Moe Z. Win are with the Laboratory for Information and Decision Systems (LIDS), Massachusetts Institute of Technology, Room 32-D674, 77 Massachusetts Avenue, Cambridge, MA 02139 USA (e-mail: shenyuan@mit.edu,moewin@mit.edu).

³The durations of normal CP and S-SCH symbol in LTE systems are approximately 4.7 us and 67 us, respectively. Although typical delay spread in cellular networks may be larger than 4.7 us, the theory and algorithm developed for semi-synchronous systems will still serve as a good approximation if the delay spread is significantly less than the duration of the S-SCH symbol (larger delay causes loss of signal energy and introduces inter-symbol interference).

II. PROBLEM FORMULATION

In this section, we describe the network models and channel models for NCS, and we then formulate the problem of NCS.

A. Channel Model

Consider a network consisting of N_{total} different cells with distinct cell IDs denoted by the set $\mathcal{N}_{\text{T}} = \{1, \ldots, N_{\text{total}}\},^5$ and a UE surrounded by N_{e} cells, denoted by the set \mathcal{N}_{E} , such that $\mathcal{N}_{\text{E}} \subseteq \mathcal{N}_{\text{T}}$ and $|\mathcal{N}_{\text{E}}| = N_{\text{e}}$. Note that in this paper the notion of neighboring cells includes both the serving base station and neighboring base stations.

In semi-synchronous systems, the information of neighboring cell IDs is captured within one S-SCH symbol. We consider two channel models in this paper: flat-fading and multipath channels. In flat-fading channel model, the received signal in frequency domain is

$$\mathbf{r} = \sum_{m \in \mathcal{N}_{\mathrm{E}}} \alpha_m \, \mathbf{G}(\tau_m) \, \mathbf{s}_m + \mathbf{z} \,, \tag{1}$$

where $\mathbf{s}_m \in \mathbb{R}^{64}$, α_m , and τ_m are the normalized S-SCH sequences of the *m*th base station, and the amplitude and delay of the signal from that base station, respectively;

$$\mathbf{G}(\tau_m) = \operatorname{diag}\left\{1, e^{-j \, 2\pi \, \Delta f \, \tau_m}, \dots, e^{-j \, 2\pi \, 63 \, \Delta f \, \tau_m}\right\}$$

in which $\Delta f = 15$ KHz for LTE systems; and z is complex white Gaussian noise with $CN(0, \sigma_z^2 \mathbf{I})$. Similarly, in multipath channel model, the received signal in frequency domain is

$$\mathbf{r} = \sum_{m \in \mathcal{N}_{\mathrm{E}}} \sum_{l=1}^{L_m} \alpha_m^{(l)} \, \mathbf{G}(\tau_m^{(l)}) \, \mathbf{s}_m + \mathbf{z} \,, \tag{2}$$

where L_m is the number of multipath components (MPCs),⁶ and $\alpha_m^{(l)}$ and $\tau_m^{(l)}$ are the amplitude and delay of the *l*th path, respectively.

For the same received signal power, detection in multipath channels is more involved than that of flat-fading channel. By comparing (1) with (2), we can see that MPCs can be thought of as signals from multiple base stations with the same S-SCH sequence through flat-fading channels, while joint detection by combining the energy from MPCs will improve the detection performance.

B. Optimal NCS Detector

When prior knowledge of neighboring cells is not available, the optimal NCS detector is the maximum likelihood estimator (MLE), given by

$$\hat{\mathcal{N}}_{E} = \arg \max_{\mathcal{N}_{E} \subseteq \mathcal{N}_{T}} \Lambda \left(\mathbf{r} | \mathcal{N}_{E} \right) \,, \tag{3}$$

⁵The set $N_{\rm T}$ contains all candidate cells, and the typical number of cells in a LTE system is $N_{\rm total} = 504$.

⁶The number of MPCs depends on the operating environments. A typical cellular channel model assumes two to three dominant MPCs [10], [11].

where $\hat{\mathcal{N}}_{E}$ is the optimal subset of cells based on the observation **r**. For example, in flat-fading channels, the likelihood can be written as [12], [13],

$$\Lambda(\mathbf{r}|\mathcal{N}_{\rm E}) \propto \exp\left\{\frac{2\mathfrak{Re}\left\{\left\langle\sum_{k\in\mathcal{N}_{\rm E}}\alpha_k \,\mathbf{G}(\tau_k) \,\mathbf{s}_k, \mathbf{r}\right\rangle\right\}}{2\,\sigma_z^2} - \frac{\left\|\sum_{k\in\mathcal{N}_{\rm E}}\alpha_k \,\mathbf{G}(\tau_k) \,\mathbf{s}_k\right\|^2}{2\,\sigma_z^2}\right\}.$$

On the other hand, when prior knowledge of neighboring cells is available, the optimal NCS detector becomes the maximum a posterior (MAP) estimator.

We focus on the MLE case in this paper and the analysis for the MAP case follows a similar process with a slight modification. Note that the MLE for NCS detection requires high computation due to a large number of hypotheses and parameters. Hence, we will first investigate the optimal detection algorithm for a single cell and then suboptimal detection algorithms for multiple cells.

III. OPTIMAL SINGLE-CELL DETECTION

In this section, we will derive the sufficient signal metric (SSM) for single-cell detection in both flat-fading and multipath channels, followed by a discussion on detection using multiple observations over time (multiple radio frames) and/or space (multiple antennas).

A. Single-Cell Detection in Flat-Fading Channels

Consider a network with only one cell, i.e., $|\mathcal{N}_{\rm E}| = 1$. The hypothesis for cell $k \in \mathcal{N}_{\rm T}$ is given by

$$H_k: \mathbf{r} = \alpha_k \mathbf{G}(\tau_k) \mathbf{s}_k + \mathbf{z},$$

and the optimal detection employs likelihood-ratio test (LRT) with the decision rule

$$\hat{k} = \arg\max_{k} \Lambda\left(\mathbf{r}|H_k\right). \tag{4}$$

Unlike conventional hypothesis testing problem, the channel parameters α_k and τ_k are unknown here, and the conditional likelihood of **r** given α_k and τ_k is given by

$$\Lambda \left(\mathbf{r} | H_k, \alpha_k, \tau_k \right) \propto \\ \exp \left\{ \frac{2 \Re \mathfrak{e} \left\{ \left\langle \alpha_k \, \mathbf{G}(\tau_k) \, \mathbf{s}_k, \mathbf{r} \right\rangle \right\}}{2 \, \sigma_z^2} - \frac{\left\| \alpha_k \, \mathbf{G}(\tau_k) \, \mathbf{s}_k \right\|^2}{2 \, \sigma_z^2} \right\}. \tag{5}$$

We now derive the SSM for the cases with and without prior channel knowledge in the following.

1) Case without Channel Knowledge: When channel knowledge is not available, i.e., α_k and τ_k are deterministic unknown parameters, the likelihood of each hypothesis by joint detection and estimation becomes the maximum likelihood over the unknown channel parameters. The corresponding result is given in the following proposition. We omit the proof here for brevity.

Proposition 1: When channel knowledge is not available, the likelihood $\Lambda_{\text{NoCh}}(\mathbf{r}|H_k)$ is

$$\Lambda_{\text{NoCh}}\left(\mathbf{r}|H_{k}\right) \propto \max_{\tau_{k}} \exp\left\{\frac{|\mathcal{F}(\tau_{k};\mathbf{s}_{k},\mathbf{r})|^{2}}{2\sigma_{z}^{2}}\right\},\qquad(6)$$

where $\mathcal{F}(\tau_k; \mathbf{s}_k, \mathbf{r})$ is the discrete-time Fourier transform (DTFT) of vector $\mathbf{r}^* \otimes \mathbf{s}_k$ evaluated at τ_k . Moreover, the ML estimate for the amplitude is given by

$$\hat{\alpha}_k = \arg \max_{\alpha_k} \Lambda \left(\mathbf{r} | H_k, \alpha_k, \tau_k \right) = \langle \mathbf{G}(\tau_k) \, \mathbf{s}_k, \mathbf{r} \rangle \; .$$

Remark 1: When channel knowledge is not available, the optimal single-cell detection is to find the largest $\Lambda_{\text{NoCh}}(\mathbf{r}|H_k)$, which is equivalent to finding the largest $\max_{\tau_k} |\mathcal{F}(\tau_k; \mathbf{s}_k, \mathbf{r})|^2$ as follows:

$$\hat{k}_{\text{NoCh}} = \arg\max_{k} \max_{\tau_{k}} \left| \mathcal{F}(\tau_{k}; \mathbf{s}_{k}, \mathbf{r}) \right|^{2} .$$
(7)

Note that the sufficient statistic for single-cell detection is the maximum value of the DTFT of $\mathbf{r}^* \otimes \mathbf{s}_k$ over different τ_k . In the following, we define this statistic as SSM. Thus for implementation, one first calculates the DTFT of the point-wise multiplication of \mathbf{r} and \mathbf{s}_k , and then chooses the maximum of the squared DTFT to be the likelihood of H_k .

2) Case with Channel Knowledge: When the parameters α_k and τ_k are mutually independent and have prior distribution $f(\alpha_k)$ and $f(\tau_k)$, the likelihood of hypothesis H_k can be derived as

$$\Lambda_{\rm Ch}\left(\mathbf{r}|H_k\right) = \int \int \Lambda\left(\mathbf{r}|H_k, \alpha_k, \tau_k\right) f\left(\alpha_k\right) f\left(\tau_k\right) d\alpha_k \, d\tau_k \,.$$
(8)

Note that the likelihood (8) depends on the specific distribution of channel parameters. For example, in the case of Rayleigh fading channel, we can simplify the likelihood (8) in the following proposition.

Proposition 2: In a Rayleigh fading channel, i.e., amplitude $|\alpha_k| \sim \text{Rayleigh}(\sigma_k)$, the likelihood $\Lambda(\mathbf{r}|H_k)$ is given by

$$\Lambda_{\text{Rayl}} (\mathbf{r} | H_k) \propto \frac{1}{1 + \sigma_k^2 / \sigma_z^2}$$
(9)

$$\cdot \int f(\tau_k) \exp\left\{ \frac{\left| \mathcal{F}(\tau_k; \mathbf{s}_k, \mathbf{r}) \right|^2}{2\sigma_z^2} \cdot \frac{1}{1 + \sigma_z^2 / \sigma_k^2} \right\} d\tau_k \,.$$

Remark 2: In the case of Rayleigh fading channels, Proposition 2 provides a simplified formula of the likelihood (equivalently, the SSM) in (8) for single-cell detection. This approach reduces the computation from two layers of integrals into one.

Note that since the captured S-SCH symbol is of duration $1/\Delta f$, τ_k can only be between 0 and $1/\Delta f$. Hence, we consider a special case when the distribution of delay τ_k is uniform on $[0, 1/\Delta f)$, and $\sigma_k^2 = \sigma_0^2$ for all $k \in \mathcal{N}_T$. Then, the likelihood of H_k in (9) reduces to

$$\Lambda_{\text{Rayl_Unif}}\left(\mathbf{r}|H_{k}\right) \propto \int_{0}^{1/\Delta f} \exp\left\{\frac{\left|\mathcal{F}(\tau_{k};\mathbf{s}_{k},\mathbf{r})\right|^{2}}{2\sigma_{z}^{2}(1+\sigma_{z}^{2}/\sigma_{0}^{2})}\right\} d\tau_{k} \,.$$

$$(10)$$

The original problem is not a canonical detection problem, since it requires estimating the unknown channel parameters (both with and without a priori knowledge) and detecting the cell simultaneously. Proposition 1 provides the SSM for NCS in flat-fading channel when channel knowledge is not available. Although SSMs for general channel knowledge in (8) is not in closed-form, Proposition 2 provides the SSM when the fading is Rayleigh.

B. Single-Cell Detection in Multipath Channels

In multipath channels, the conditional likelihood becomes

$$\Lambda(\mathbf{r} | H_k, \boldsymbol{\alpha}_k, \boldsymbol{\tau}_k) \propto \exp\left\{\frac{2\Re \left\{\left\langle \sum_{l=1}^{L_k} \alpha_k^{(l)} \mathbf{G}(\boldsymbol{\tau}_k^{(l)}) \mathbf{s}_k, \mathbf{r} \right\rangle \right\}}{2 \sigma_z^2} - \frac{\left\| \sum_{l=1}^{L_k} \alpha_k^{(l)} \mathbf{G}(\boldsymbol{\tau}_k^{(l)}) \mathbf{s}_k \right\|^2}{2 \sigma_z^2}\right\}, \quad (11)$$

where $\alpha_k = [\alpha_k^{(1)} \alpha_k^{(2)} \cdots \alpha_k^{(L_k)}]$ and $\tau_k = [\tau_k^{(1)} \tau_k^{(2)} \cdots \tau_k^{(L_k)}]$. It is difficult to further simplify the likelihood function $\Lambda(\mathbf{r} | H_k)$ obtained from (11) for general multipath channels. Hence, we will consider discrete-time channels where inter-arrival times of the MPCs are multiplications of $1/(64\Delta f)$, i.e., all the arrival time can be expressed as

$$\tau_k^{(l)} \in \left\{ \frac{j}{64\,\Delta f} + \tau^* \, \big| \, j \in \mathbb{Z}^+ \cup \{0\} \right\} \,, \tag{12}$$

where τ^* is a constant. Then the MPCs can be shown orthogonal to each other, such that

$$\left\langle \mathbf{G}(\tau_k^{(l)}) \, \mathbf{s}_k, \mathbf{G}(\tau_k^{(n)}) \, \mathbf{s}_k \right\rangle = \delta_{ln} \, .$$

With this assumption, the conditional likelihood in (11) becomes

$$\begin{split} &\Lambda(\mathbf{r} \left| H_k, \boldsymbol{\alpha}_k, \boldsymbol{\tau}_k \right) \propto \\ &\exp\left\{ \frac{2 \mathfrak{Re}\left\{ \left\langle \sum_{l=1}^{L_k} \alpha_k^{(l)} \, \mathbf{G}(\boldsymbol{\tau}_k^{(l)}) \, \mathbf{s}_k, \mathbf{r} \right\rangle \right\}}{2 \, \sigma_z^2} - \frac{\sum_{l=1}^{L_k} \left| \alpha_k^{(l)} \right|^2}{2 \, \sigma_z^2} \right\}. \end{split}$$

Following a similar derivation as that in the previous section, we have the following results.

Proposition 3: Assume that inter-arrival times of the MPCs are multiplications of $1/(64\Delta f)$. When channel knowledge is not available, the likelihood $\Lambda_{\text{NoCh}}(\mathbf{r} | H_k)$ for multipath channels is given by

$$\Lambda_{\text{NoCh}}(\mathbf{r} | H_k) \propto \max_{\boldsymbol{\tau}_k} \sum_{l=1}^{L_k} \left| \mathcal{F}(\tau_k^{(l)}; \mathbf{s}_k, \mathbf{r}) \right|^2.$$
(13)

Proposition 4: Assume that inter-arrival times of the MPCs are multiplications of $1/(64\Delta f)$. For independent Rayleigh fading channels with $|\alpha_k^{(l)}| \sim \text{Rayleigh}(\sigma_k^{(l)})$, the likelihood $\Lambda_{\text{Rayl}}(\mathbf{r} | H_k)$ for multipath channels is given by

$$\Lambda_{\text{Rayl}}(\mathbf{r} | H_k) \propto \prod_{l=1}^{L_k} \frac{1}{1 + \sigma_k^{(l) \, 2} / \sigma_z^2}$$
(14)

$$\cdot \int f(\boldsymbol{\tau}_k) \exp\left\{ \sum_{l=1}^{L_k} \frac{\left| \mathcal{F}(\boldsymbol{\tau}_k^{(l)}; \mathbf{s}_k, \mathbf{r}) \right|^2}{2 \, \sigma_z^2 \left(1 + \sigma_z^2 / \sigma_k^{(l) \, 2}\right)} \right\} \, d\boldsymbol{\tau}_k \, .$$

Furthermore, if 1) $\tau_k^{(l)}$'s are independent and uniform on $[0, 1/\Delta f)$ and 2) $\sigma_k^{(l)} = \sigma_0^2$ for all k and l, (14) can be approximated by (13).

Remark 3: Propositions 3 and 4 have shown some simplified forms of the likelihood under the assumption that MPCs

are orthogonal to each other. When the channel knowledge is not available, the likelihood of cell k is the sum of the largest L_k taps of $|\mathcal{F}(\tau_k^{(l)}; \mathbf{s}_k, \mathbf{r})|^2$; while the likelihood becomes (14) for Rayleigh fading channels where the amplitude $\alpha_k^{(l)}$'s are mutually independent. Note that the delay constant τ^* in (12) is a parameter that can be tuned to better capture the MPCs.

C. Single-Cell Detection with Multiple Observations

We have so far discussed the optimal cell search with a single observation. Multiple observations over time (multiple radio frames) and/or space (multiple antennas) can be combined coherently or incoherently to improve the system performance [14], [15]. The received signals from different observations are written as

$$\mathbf{r}[t] = \sum_{k \in \mathcal{N}_{\rm E}} \sum_{l=1}^{L_k[t]} \alpha_k^{(l)}[t] \, \mathbf{G}(\tau_k^{(l)}[t]) \, \mathbf{s}_k + \mathbf{z}[t], \ t = 1, \dots, N_{\rm ob} \,,$$

where t is the index of multiple observations. Since observation noises are independent, the log-likelihood with all observations is equal to the sum of individual log-likelihood, i.e.,

$$\ln \Lambda(\mathbf{r} | H_k) = \sum_{t=1}^{N_{\rm ob}} \ln \Lambda(\mathbf{r}[t] | H_k).$$

After some algebra, we can derive the likelihood for the case when channel knowledge is not available. Three different scenarios are considered as follows.

Case 1: when both $\tau_k^{(l)}[t]$ and $\alpha_k^{(l)}[t]$ are the same over different t, the likelihood with multiple observations is

$$\Lambda(\mathbf{r} | H_k) \sim \max_{\boldsymbol{\tau}_k} \sum_{l=1}^{L_k} \left| \mathcal{F}(\tau_k^{(l)}; \mathbf{s}_k, \sum_{t=1}^{N_{ob}} \mathbf{r}[t]) \right|^2.$$
(15)

This scenario corresponds to additive white Gaussian noise (AWGN) channels where channels are deterministic and timeinvariant, and hence the observations can be combined coherently.

Case 2: when $\tau_k^{(l)}[t]$ are the same and $\alpha_k^{(l)}[t]$ are independent over different t, the likelihood with multiple observations is

$$\Lambda(\mathbf{r} | H_k) \sim \max_{\boldsymbol{\tau}_k} \sum_{l=1}^{L_k} \left(\sum_{t=1}^{N_{ob}} \left| \mathcal{F}(\boldsymbol{\tau}_k^{(l)}; \mathbf{s}_k, \mathbf{r}[t]) \right|^2 \right) \,. \tag{16}$$

This scenario corresponds to independent fading for different observations, but the arrival times of the MPCs remain the same throughout the observation interval. This case is of most interest since it is closest to most cellular environments. Moreover, note that when observations are made within coherence time or space, i.e., $\alpha_k^{(l)}[t]$'s are correlated, the likelihood will be between (15) and (16).

Case 3: when both $\tau_k^{(l)}[t]$ and $\alpha_k^{(l)}[t]$ are independent over different t, the likelihood with multiple observations is

$$\Lambda(\mathbf{r} | H_k) \sim \sum_{t=1}^{N_{ob}} \max_{\boldsymbol{\tau}_k[t]} \sum_{l=1}^{L_k[t]} \left| \mathcal{F}(\boldsymbol{\tau}_k^{(l)}[t]; \mathbf{s}_k, \mathbf{r}[t]) \right|^2$$

This scenario corresponds to the case that the UE has moved for a certain distance in the observation interval and the likelihood is combined incoherently.

Remark 4: With multiple observations, the cell search process can exploit temporal and/or spatial diversity to provide better performance for cell detection. Note that in interference-limited environments, the interference also combines coherently and thus degrades the benefit of combining multiple observations. Moreover, the likelihood for the cases where channel knowledge is available can be derived similarly as in Section III-B, and we omit them here for brevity.

IV. MULTI-CELL DETECTION

In this section, we will derive the SSM for multi-cell detection. The discussion will mainly focus on the case where channel knowledge is not available, which can be extended to the case with channel knowledge as shown in Section III-B.

A. Optimal Search Strategy

The optimal search strategy for multi-cell detection uses the MLE given in (3). For a given number of neighboring cells $|\mathcal{N}_{\rm E}| = N_{\rm e}$, there are $K(N_{\rm e}) \triangleq N_{\rm total}!/(N_{\rm e}!(N_{\rm total} - N_{\rm e})!)$ different possible subsets of cells, and each of the subsets forms a hypothesis \tilde{H}_p , where $p = 1, \ldots, K(N_{\rm e})$. Let $\tilde{\Lambda}(N_{\rm e})$ denote the maximum of these hypotheses' likelihoods:

$$\tilde{\Lambda}(N_{\rm e}) \triangleq \max_{p} \Lambda\left(\mathbf{r}|\tilde{H}_{p}\right),$$
(17)

where each individual likelihood is given by

$$\Lambda\left(\mathbf{r}|\tilde{H}_{p}\right) = \max_{\boldsymbol{\alpha}_{k},\boldsymbol{\tau}_{k}}\Lambda\left(\mathbf{r}\left|\tilde{H}_{p},\{\boldsymbol{\alpha}_{k},\boldsymbol{\tau}_{k},k\in\mathcal{N}_{\mathsf{E}}^{p}\}\right)\,,$$

in which \mathcal{N}_{E}^{p} denotes the subset of cells associated with hypothesis \tilde{H}_{p} . The subset of cells corresponding to $\tilde{\Lambda}(N_{e})$ provides the MLE of neighboring cells for a given N_{e} .

The likelihood $\overline{\Lambda}(N_e)$ increases (the residual decrease) with both N_e and L_k since it provides more degrees of freedom for fitting. Hence, in order to avoid over-fitting,⁷ we need to impose constraints or termination rules on the search process. Two types of constraints are proposed: first, $|\mathcal{N}_E| = N_{\text{max}}$ is fixed based on the prior knowledge of the maximum detectable cells, such as the deployment of base stations; second, we incrementally raise the cardinality of the subset \mathcal{N}_E until the residual is close to the noise power.

Large number of hypotheses makes the MLE for optimal multi-cell search computationally prohibitive. In the following sections, we will propose sub-optimal implementable algorithms.

B. Successive Detection

We now propose sub-optimal implementable cell search algorithms using successive detection. Successive multi-cell detection is decision-aided and decomposes each step to channel estimation and single-cell detection, where zero-forcing (ZF), matched filter (MF), or minimum mean squared error

⁷In LTE systems, the cardinality $|\mathcal{N}_{T}| = 504$ is much larger than the dimension of the received signal vector (length-64).

(MMSE) methods may be applied [10]. Neighboring cells are detected using single-cell detection techniques after the signals of the detected cells are removed through channel estimation, i.e., successive interference cancellation (SIC).

1) Channel Estimation: SIC removes the signals of detected cells from the received signal, which provides those undetected cells a higher signal-to-inference-plus-noise ratio (SINR) and thus a better detection probability. For example in flat fading channels, the received signal can be written as

$$\mathbf{r} = \mathbf{S} \, \boldsymbol{\alpha} + \mathbf{z}$$
,

where α is the vector of the amplitudes of the signals, **S** is a matrix whose columns are the $\mathbf{G}(\tau_m)\mathbf{s}_m$ of the detected cells, and **z** is the noise plus the interference from undetected cells. Channel estimates using MMSE and ML are given, respectively, by

$$\begin{split} \hat{\boldsymbol{\alpha}}_{\text{MMSE}} &= \mathbf{R}_{\boldsymbol{\alpha}}^{\frac{1}{2}} \, \left\{ \mathbf{R}_{\boldsymbol{\alpha}}^{\frac{1}{2}} \, \mathbf{S}^{\dagger} \, \mathbf{S} \, \mathbf{R}_{\boldsymbol{\alpha}}^{\frac{1}{2}} + \sigma_{z}^{2} \, \mathbf{I} \right\}^{-1} \, \mathbf{R}_{\boldsymbol{\alpha}}^{\frac{1}{2}} \, \mathbf{S}^{\dagger} \, \mathbf{r} \, , \\ \hat{\boldsymbol{\alpha}}_{\text{ML}} &= \left(\mathbf{S}^{\dagger} \, \mathbf{S} \right)^{-1} \, \mathbf{S}^{\dagger} \, \mathbf{r} \, , \end{split}$$

where $\mathbf{R}_{\alpha} = \mathbb{E} \{ \alpha^{\dagger} \alpha \}$ is the cross-correlation matrix of α . Both average squared estimation errors using MMSE and ML are shown approximately equal to the noise power, i.e., $\mathbb{E} \{ \| \alpha - \hat{\alpha} \|^2 \} \approx N_{e} \cdot \sigma_z^2$ [6]. Note that channel estimates can be used in other applications, such as location inference from the path gain through received signal strength indicator and delays through time-difference-of-arrival [16], [17].

2) Successive Cell Detection: The residual signal after cancellation is

$$\tilde{\mathbf{r}} = \sum_{m \in \tilde{\mathcal{N}}_{\mathsf{E}}} \left[\alpha_m \, \mathbf{G}(\tau_m) - \hat{\alpha}_m \, \mathbf{G}(\hat{\tau}_m) \right] \mathbf{s}_m + \alpha_k \, \mathbf{G}(\tau_k) \, \mathbf{s}_k + \mathbf{z} \,,$$

where $\tilde{\mathcal{N}}_{\rm E}$ is the set of detected cells, $\hat{\alpha}_m$ and $\hat{\tau}_m$ are channel estimates, $k \in \mathcal{N}_{\rm T} \setminus \tilde{\mathcal{N}}_{\rm E}$, and z is the noise plus unknown interference modeled as complex Gaussian. The algorithm then detects the next cell \mathbf{s}_k based on the residual signal $\tilde{\mathbf{r}}$. Three different types of detector can be applied, i.e., ZF, MF, and MMSE.

In ZF detector, candidate S-SCH symbol with delays are orthogonalized with those of detected cells before matching the *original* signal **r**. The ZF detector usually perform well in high SINR regions, and it also suppresses the propagation of amplitude estimation errors in successive detection for NCS. In MF detector, candidate S-SCH symbol with delays are directly used for matching the *residual* signal $\tilde{\mathbf{r}}$. The MF detector has the advantage of good performance in low SINR, but poor cross-correlation property of S-SCH sequences induces strong interference in NCS. The MMSE detector is implemented by a whitening filter plus a MF. The MMSE detector maximizes the SINR,⁸ and hence outperforms bother ZF and MF in successive MUD. Nevertheless, the MMSE detector still suffers from channel estimation errors.



Fig. 1. Performance of the NCS algorithm using multiple antennas. The simulation is based on the GSM TU3 channel and $N_{\text{total}} = 500$.

V. SIMULATION RESULTS

In this section, we provide simulation results to verify our analysis and evaluate the performance of the proposed algorithms. The received signals from 57 cells with wraparound structure are generated on the multi-cell link level simulator.⁹

We first examine the performance gain of combining the observations from the multiple receive antennas at UE in GSM TU3 channel. Each UE is equipped with two antennas according to the LTE standard, and Fig. 1 shows the number of detected cells by a single antenna and dual antennas in a network with $N_{\text{total}} = 500$. For each individual antenna, the numbers of correctly detected cells fluctuates due to fast fading in different radio frames. However, the performance improves significantly and becomes more stable when combining the observations from the two antennas since spatial diversity is exploited in fading channels. Note that one more cell can be detected on average with dual antennas than with a single antenna.

We then investigate the performance of the NCS algorithm at different UE locations in GSM TU3 channel. Figure 2 shows the number of detected cells as a function of the total number of cells for a UE located at cell edge, middle, and center.¹⁰ Several observations can be drawn from the figure. First of all, the UE at the cell edge can detect most neighboring cells, since the UE is closer to its neighboring cells and hence has a good signal reception from neighboring cells. This area is indeed of most interest because the UE may need to handover to another base station. Second, the number of detected cells decreases when the UE locates in the middle area of the cell, since the signal powers from the neighboring cells drops. Surprisingly, better performance is achieved for the UE at the center than in the middle of the cell. This can be explained as follows: at cell center, the UE has a good reception from the serving cell, and hence it can obtain a better channel estimate of the serving cell for interference cancellation; this effectively improves the SINR for other neighboring cells, although the receive signal

⁸Note that maximizing SINR is equivalent to MMSE receiver with an appropriate scaling [10].

⁹The multi-cell simulator is developed by Qualcomm Inc., and has capability to simulate both flat fading and multipath fading channels with different UE mobility.

¹⁰Within a cell, the position of UE is called at cell edge, middle, and center as it locates towards the center of the cell from boundary.



Fig. 2. Average number of detected cells at different UE locations, i.e., cell edge, middle, and center.

powers from neighboring cells are relatively lower than those when the UE is in the cell middle.

We finally examine the performance of the NCS algorithm with observations in multiple radio frames. Figure 3 shows the number of detected cell as a function of the number of radio frames with a single and two receive antennas. Multiple observations not only increase the SNR of the desired signal, but also provide temporal diversity, and hence the number of detected cells increases with the number of radio frames. Since higher UE speed results in faster channel variation in consecutive frames, the observations by a high-speed UE are less correlated, resulting in the better performance of the NCS algorithm, especially when only limited number of observations is available. On the other hand, for multi-antenna systems, the gain from multiple observations in time is less significant because diversity has already been exploited in space. The performance gain is diminishing as more observations are incorporated, since diversity has been fully exploited and the performance becomes limited by interference.

VI. CONCLUSION

In this paper, we investigate the NCS problem for the LTE systems. We first derived the SSMs for cell search in both flat-fading and multipath channels and then developed NCS algorithms based on the SSMs. Our theory and algorithm also account for multiple observations over time (multiple radio frames) and/or space (multiple antennas). Combining multiple observations increases the received signal's SNR and provides diversity for cell detection, which has been shown to improve the NCS performance significantly both in theory and by simulations, especially in slow channel-variation environments.

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Fig. 3. Cell search with multiple observations ($N_{\text{total}} = 500$). Performance with different number of antennas is investigated at different UE speed (3 km/h, 30 km/h, and 120 km/h).

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