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Leveraging Massive MIMO Spatial Diversity in Random Access

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ABSTRACT

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Random access is a crucial building block for nearly all wireless networks, and impacts both the overall spectral efficiency and latency in communication. In next-generation networks, it is expected that diverse new services will be served by cellular networks, e.g. connections to Unmanned-Air-Vehicles (UAVs) and Internet-of-Things (IoT) devices, potentially increasing the node density served per base-station. Higher node density implies increased latency in random access operation, due to increased packet collision events.

In this thesis, we show via analytical evaluation and monte-carlo simulations that the large spatial degrees of freedom available in massive MIMO systems can potentially be leveraged to reduce random access latency. We show that with large arrays, the spatial channel “codes” of each user are also potentially separable, providing another avenue for the receiver to distinguish overlapping users in the angle-of-arrival domain. First, using one-ring propagation model, we evaluate how the random access collision probability depends on the aperture size of the array and the spread of user’s signal angle-of-arrivals at the base-station, as a function of the user-density and the number of random access codes. Then, in order to practically achieve the analytical performance bounds, we present a simple clustering algorithm inspired by the channel parameters obtained from experimental studies on UAV’s air-to-base station channel
and on LTE’s 3GPP channel model for ground-to-base station traffic.

Our numerical evaluations show that depending on the scattering environment and antenna array size, we can attain $2.4 \times$ to $6.8 \times$ reduction in collision probability. The result of evaluating our algorithm on UAV’s air to base-station channel shows that as a function of node density $1.7 \times$ to $3.5 \times$ reduction in collision probability is possible with practical array sizes. Moreover, we also show that with parameters from LTE’s 3GPP channel model, nearly $1.4 \times$ to $2.3 \times$ reduction in collision probability is achievable using our proposed algorithm.
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Chapter 1

Introduction

1.1 Basics of Random Access

Random access is an essential element in many wireless networks. A successful random access operation is analogous to a handshake; it precedes the actual communication and makes the receiving station aware of a transmitting station in its vicinity, attempting to communicate with it using its data. For example, IEEE 802.11 (WiFi) standards rely on random access with binary exponential backoff for data transmissions. In cellular networks, clients send access request for uplink resources to the base-station via a Random Access CHannel (RACH [1]). This request utilizes a combination of code-division multiple access and exponential backoff. This code dimension is used to reduce the collision probability compared to a random access system (e.g. WiFi) where all nodes essentially use the same code overlapped in time and frequency.

1.2 Next-generation Data Traffic

In the next-generation networks, the node density per unit cell is expected to grow significantly. The increased density will come from a variety of new sources, such as Unmanned-Air-Vehicles (UAVs) (also known as drones), and Internet-of-Things (IoT) devices. In not-so-distant future, drones may also act as ad hoc base-stations and will be used to assist the existing cellular infrastructure in cases of increased user demand,
e.g. in case of a football game or a concert, or in cases of natural disasters when the existing infrastructure has been destroyed; e.g. Facebook, Google and SpaceX are exploring methods to provide internet connectivity to remote areas using drones [2]. Other uses of drones include border surveillance, news coverage, aerial photography, search and rescue operations, storm tracking and terrain mapping of inaccessible locations. Consider for example statistics from market survey company Tractica, which predicts that by 2025 the shipment of commercial drones is expected to reach 2.7 million [3]. This explosive increase in the use of drones in air will compete for resources with massive number of internet-of-things devices on ground. According to predictions by research firm BI Intelligence, as compared to 2016’s 6.6 billion devices, there will be 22.5 billion devices connected in 2021 through internet-of-things [4].

Due to these aforementioned reasons, it is reasonable to assume that we are looking towards a future with diverse forms of traffic. i.e. at any random time, a human user may pull out her cellphone to demand services from the base-station or a drone might have to relay in real-time coverage of an important event happening or an internet-of-things device might have to report time critically a breach in a security surveillance system.

However, due to the broadcast nature of the wireless medium, if multiple users send concurrent in-band transmissions, this would cause interference due to superposition of their transmissions and their data will not be decodable by the base-station, a well known phenomenon known as collisions. The root cause of collisions in random access is that the packet arrival times at different devices is random, hence, their requests can not be scheduled a priori. Moreover, node activity can be intermittent and, therefore, the base-station needs to allocate resources to serve active users with limited number of available data slots.
1.3 Random Access in LTE

To handle concurrent random access user requests, current LTE standard specifies 64 orthogonal codes for accessing the base-station. The users randomly pick a code from a pool of 64 and send association request, during LTE Random Access CHannel (RACH) time-frequency slot, to the base-station for subsequent data transfer. If more than one users pick up the same code, it causes collision at the base-station and necessitates further steps for collision resolution that add to the latency in connecting users to the base-station.

Steps of random access protocol in LTE:

The random access protocol in LTE is shown in Fig. 1.1 and consists of the following steps:

Step 1: Users randomly pick a code from a predefined set of 64 codes. This code

![Diagram of LTE random access protocol](image)

Figure 1.1 : LTE random access protocol.
serves as a preamble and helps base-station to gain synchronization with the users. Since users pick preambles in an uncoordinated way, a collision occurs when more than one users pick the same code. Any collision occurring at this step goes undetected as base-station only detects if a particular preamble has been activated or not [5].

**Step 2:** In this step, base-station sends a random access response to the users and conveys parameters like timing advance and allocates a data transmission resource block to the users who activated the preambles.

**Step 3:** Each user that received the random access response from the second step sends a Radio Resource Control (RRC) connection request. But if more than two users activated the same preamble in Step 1 of random access, they send their RRC request in the same resource block, causing a collision at the base-station. The base-station replies only to the random access requests that did not experience a collision [6].

**Step 4:** Having received no response from the base-station, the colliding users repeat the above process after a random back-off time. This back-off following a collision event is the major source of latency in connecting users to the base-station.

Fig. 1.2 shows the collision probability of LTE random access system with 64 codes as a function of number of users in the cell. Fig. 1.2 shows that even with 10 users, the probability of collision is 50%, which means that in nearly half of the random access attempts, two or more users will pick the same code/codes. Hence, in this thesis we ask this question that can we improve the efficiency of random access without increasing the bandwidth or time allocated for random access in LTE?

### 1.4 Solution for Improving Random Access

Our main contribution in this thesis is to show that random access collisions can be reduced with the large number of spatial degrees of freedom provided by massive
MIMO base-stations, e.g. those that will be present in 5G networks. The key insight is that in base-stations with large number of antennas, there is an added capability of estimating the angle-of-arrivals of incoming signals.

To see how this feature can benefit random access, consider Fig. 1.3 where a user $U_1$ is transmitting from a location with an angle of $\phi_1$ with the base-station and another user $U_2$ is transmitting at an angle of $\phi_2$ with the base-station. If $\phi_1$ is *sufficiently apart* from $\phi_2$ (we define what we mean by *sufficiently apart* in Section 2), then angular separation $\Delta_\phi = \phi_2 - \phi_1$ between them can be leveraged to simultaneously identify the presence of two users attempting to associate with the base-station even if they transmitted the same code over-lapped in time and frequency, an event which would otherwise have resulted in a collision in the current random access systems.
Figure 1.3 : Example of using spatial dimension to identify users even if they use the same code.

1.5 Challenges

While we can estimate the angle-of-arrival of a planewave or a superposition of planewaves using the super-resolution algorithms like MUSIC [7] or ESPRIT [8] or their variants [9], the spatial channel codes of two users can also “collide” due to the following reasons:

- **Multiple paths**: When a communication signal passes through a wireless channel, it bounces off the scatterers and spreads. Thus, due to this multipath “spreading” of signal, the angle-of-arrivals of two users might merge and appear to be coming as just one user without displaying any signs of angular separation, as shown in Fig. 1.4a.

- **Finite antenna resolution**: The angular resolution capability of practical
(a) Collision due to multipath

(b) Collision due to finite antenna resolution

Figure 1.4: Sources of collisions in spatial domain.

antenna aperture sizes is finite. This means that two users can be sufficiently apart from each other such that their angle-of-arrivals do not overlap, as shown in Fig. 1.4b, but the angular resolution of the antenna array at the base-station might not be sufficient to tell the angle-of-arrivals of two separate users apart. An extreme example of this phenomenon would be the case when base-station has just one antenna. In that case, the base-station cannot resolve angle-of-arrivals.

1.6 Key Contributions and Results

In this thesis, our contributions are as follows:

1. Using the well-known one-ring propagation model [10], we numerically evaluate
the collision probability of a random access system which has user density $\rho$, area of the plane $A$, circular antenna with aperture of radius $R$, user-signal angle-of-arrival spread confined to a radius $r$ due to one-ring model and the number of orthogonal codes being $L$. We derive collision probability bounds that show that in high user density scenarios, when the probability of collision of the baseline system is 98%, practical array sizes can provide $2.4 \times$ to $6.8 \times$ reduction in collision probability.

2. Next we analyze the performance of our proposed system for real-world drone to base-station channel models. In this work, we leverage the opportunity of high probability of (largely) single-path LOS channel between drones and base-station to simultaneously connect multiple drones to the base-station. Using the drone wireless propagation environment parameters for air-to-base station traffic, we show that as a function of user density $1.7 \times$ to $3.5 \times$ reduction in collision probability is possible with practical array sizes.

3. Finally, we evaluate the performance of our proposed solution using channel model parameters from LTE’s 3GPP channel model. In this channel, due to high scattering environment, we find that the angle-of-arrival from a user are only statistically bounded. But even in such a dispersive channel, depending upon number of users in the cell, nearly $1.4 \times$ to $2.3 \times$ reduction in collision probability is achievable using our proposed method.

1.7 Related Work

The issue of increased latency in connecting users to the base-station due to the failure of user-identification during random access process has been studied in prior
works. SUCR protocol [11] resolves collisions occurred in initial ranging of the LTE random access (RACH) procedure distributively at users and allows a user to continue transmitting only if it has the strongest channel to the base-station. However, apart from being unfair in certain scenarios, it does not increase the number of users that can be simultaneously resolved at the base-station (during random access) at a given time beyond the number of codes available (e.g., 64 in LTE). In contrast, in our proposed method, we not only decrease the probability of collisions but also provide a mechanism that can potentially allow more users to connect to the base-station than the maximum number of orthogonal codes available. In [12], the authors leverage multiple antennas and timing misalignment between the users’ random access request to perform collision resolution at base-station. Therefore, two or more users choosing same code and arriving at exactly the same time are not differentiable. As opposed to their scheme, our work does not necessitate any timing mismatch between the reception of the colliding users’ random access request at the base-station. In [13, 14, 15], angle-of-arrival based processing is used for mitigating pilot contamination and is paired with pilot allocation algorithms. However, pre-allocation strategy does not work for our application because user locations are random and they have intermittent activity.

In [16], detection of number signals arriving at an array is presented using information theoretic criteria, however, the signals must be non-coherent. In [17], Wax et. al. evaluate the number of coherent signals impinging on a sensor array using MDL principle. In [18], a novel method is presented for detection of a mixture of coherent and non-coherent signals based on MDL principle. However, all of these works estimate the total number of signals in coherent and non-coherent groups and not the number of non-coherent groups and the number of coherent signals in each
Another body of literature that comes close to our work is the localization of one or multiple number of users based on their angle-of-arrival information. In WiDeo [20], Joshi et. al. leverage the changes in angle-of-arrival and time-of-flight of wireless backscatter components at the WiFi access point to perform motion detection. Although their method can be used to identify multiple users simultaneously by classifying accurately the angle-of-arrivals and time-of-flight components belonging to the motions that caused them, it relies on motion to identify them and, hence, cannot identify the presence of multiple stationary users. Similarly xD-Track [21], performs motion tracking by sending out a probing signal in the environment like a flash and another receiver tries to localize a moving target user based on the angle-of-arrival, time-of-flight and doppler shift values of the received transmission. This work is different from ours as we have multiple active users at a specific time which may or may not be stationary. Another work, ArrayTrack [22] uses multiple WiFi access points distributed across a floor to localize the users but all the multipaths received at an access points are assumed to belong to just one user whereas for our work there are multiple users transmitting concurrently whose net reception reaches the base-station, a phenomenon that makes user-identification and multipath classification very difficult. Moreover, SpotFi [23] performs accurate indoor localization of a user using angle-of-arrival and time-of-flight information from a target’s signal with only three antennas. However, their solution is not directly applicable to our case as they require measurements from multiple access points relayed to a central server to perform accurate localization of a target.
1.8 Outline of the Thesis

The rest of the thesis is organized as follows. In Chapter 2, we present our system model and analyze the collision probability of \((\rho, A, r, R, L)\) random access system and compare the performance of our proposed system with the baseline cellular system under various scattering environments and antenna aperture sizes. In Chapter 3, we evaluate the probability of collision of our proposed system when we have a drone-to-base station channel model whereas in Chapter 4, we evaluate the probability of collision of our proposed system using LTE’s 3GPP channel model. Finally, the thesis is concluded in Chapter 5 with comments on future work.
Chapter 2

Probability of Collision Analysis

In this chapter, we first present our system model and then use it to perform probability of collision analysis of our proposed solution augmenting code dimension with spatial dimension to resolve collisions during random access.

2.1 System Model

We describe the three components of our system in this section; namely spatial user distribution, channel propagation model and array model.

Spatial user distribution: We assume that there is only one cell with an area $A$. We model the location coordinates $(x, y) \in \mathbb{R}^2$ of the users in the cell at any instant according to a realization of a Poisson Point Process (PPP) of density $\rho$ [24, 25]. Thus, the mean number of users in the cell at any time is given by $\rho A$.

Channel propagation model: To model the multipath propagation environment, we use one-ring model [10] which assumes that the spread in user signal angle-of-arrival seen at the base-station is only due to local scattering around the user, within a circle of radius $r$ around it.

Array model: We assume that the base-station uses a circular array, with an antenna aperture of radius $R$ at a height $z$. The circular aperture can be expressed in three-dimensional space as:

$$a(x', y', z') = c(x', y')\delta(z')$$  (2.1)
where,
\[ c(x', y') = \begin{cases} 
1, & \text{if } \sqrt{x'^2 + y'^2} \leq R \\
0, & \text{otherwise}
\end{cases} \] (2.2)

Also, we consider a narrowband system where a monochromatic planewave is incident on the circular aperture, subtending an azimuth angle \( \theta \in \left[-\frac{\pi}{2}, \frac{\pi}{2}\right] \) and elevation angle \( \phi \in \left[0, \frac{\pi}{2}\right] \).

### 2.2 Probability of Collision Analysis

In this section, we analyze the collision probability of two systems. First will be the baseline random access system which uses \( L \) codes (in LTE, \( L = 64 \) and in WiFi, \( L = 1 \)). The second system will be the proposed system which utilizes the fact that the user angle-of-arrivals are limited, allowing the base-station to resolve two users based on their angle-of-arrival differences. We analyze the proposed system in two steps. We first assume that the array aperture is infinite, and then for the general case where the array aperture is finite.

#### 2.2.1 Baseline System

The baseline system is representative of the current cellular systems which do not leverage angle-of-arrivals differentiation. Thus, in this case, the collision is defined as the event when more than one users pick the same code at the same time. For simplicity, we assume a slotted system, so either the transmission overlaps completely or does not overlap at all. Hence, the probability of collision of the baseline system
\(P_b\) is

\[
P_b = \sum_{N=2}^{\infty} P(N)P(\text{at least two users pick the same code} \mid N)
\]

\[
= \sum_{N=2}^{L} \frac{(A\rho)^Ne^{-A\rho}}{N!} \left[1 - \frac{L!}{(L-N)!} \left(\frac{1}{L}\right)^N\right] + \sum_{N=L+1}^{\infty} \frac{(A\rho)^Ne^{-A\rho}}{N!}.
\]

Note that the first part of the summation is not present when \(L = 1\).

### 2.2.2 Proposed System: Aperture \(R \to \infty\)

![Conceptual illustration of the collision event when the array aperture \(R \to \infty\).](image)

Figure 2.1: Conceptual illustration of the collision event when the array aperture \(R \to \infty\).
We start by analyzing the case when the array aperture is very large. We first depict the potential collision event pictorially in Figure 2.1, which happens when the users pick the same code and there is an overlap in their one-rings on the ground. Note that the overlap in their one-rings causes an overlap in the power-angle spectrum in the array domain, as shown in Figure 2.1, which means that the array cannot resolve the signal sources coming from different users (despite having infinite angular resolution). Then the probability of collision in this case of proposed system $P_{p,R \rightarrow \infty}$ is given by

$$P_{p,R \rightarrow \infty} = \sum_{N=2}^{\infty} P(N)P(\text{more than one users pick the same code and have overlap in one-ring} \mid N) \approx \sum_{N=J+1}^{\infty} \frac{(A\rho)^N e^{-A\rho}}{N!} \left( 1 - \frac{J!}{(J - N)!} \left( \frac{1}{J} \right)^N \right)$$

(2.4)

where $S = 4\pi r^2$ and $J = L \left\lfloor \frac{A}{S} \right\rfloor$. We will assume $r \ll \sqrt{A}$ which implies $S \ll A$ and further, we will ignore the edge effects; as a result the expression is an approximation with a small error.

### 2.2.3 Proposed System: Finite Array Aperture $R$

**Effect of finite antenna aperture**

In Figure 2.2, we conceptually depict how finite resolution due to finite array aperture increases the collision “footprint”, by increasing the overlap in the power-angle spectrum. Computing this increase is however non-trivial. The main reason is due to
non-linear mapping of the geographical space to power-angle spectrum, as explained below.

**Ground $\rightarrow$ power-angle domain:** In Figure 2.3a, we show how the one-rings on the ground map to the power-angle as a function of distance from the base-station. As evident from the Figure 2.3b, the farther the user, smaller is the angular spread in power-angle domain. We characterize this mapping next.

Consider circular disc on the ground, which consists of following points defined as set $\mathcal{D}_g$,

$$\mathcal{D}_g = \{(x, y) : \sqrt{(x - g)^2 + (y - h)^2} \leq r\}, \quad (2.5)$$
where \((g, h)\) is the center of the disk. Set \(D_g\) maps to the following set, \(D_a\), in the power-angle spectrum,

\[
D_a = \left\{ (\theta, \phi) : \theta = \tan^{-1} \left( \frac{x}{y} \right), \phi = \tan^{-1} \left( \frac{\sqrt{x^2 + y^2}}{z} \right) \right\}, \tag{2.6}
\]

where \(z\) is the height of the base-station.

**Power-angle domain \(\rightarrow\) ground:** The clear AoA \((\theta, \phi)\) spectra boundaries, as shown in Fig. 2.3b, are possible only if the users are separated from each other by more than the minimum distance specified between them by any resolvability criteria [26]; closer than that, the spectral boundaries expand and the base-station would not be able to identify the incident waves as two different planewaves. We adopt the Rayleigh resolution criteria [26].

The aperture smoothing function for a circular array is given by [26]:

\[
C(k_{xy}) = \frac{2\pi RJ_1(k_{xy}R)}{k_{xy}} \tag{2.7}
\]

where \(J_1(\cdot)\) is first order bessel function of the first kind, \(k_{xy} = \sqrt{k_x^2 + k_y^2}\), wavenum-
ber \( k_x = |k| \sin \theta \sin \phi \), wavenumber \( k_y = |k| \cos \theta \sin \phi \) and \( |k| = \frac{2\pi}{\lambda} \). From (2.7), the zeros of the aperture smoothing function occur at a radius of \( \delta k_{xy} = \frac{1.22\pi}{R} \). Hence, given that a planewave is incident on the circular aperture at bearing \((\theta_o, \phi_o)\), then according to Rayleigh criterion, the set \( F \) of all wavenumber vectors \((k^n_x, k^n_y)\) just resolvable from the incident wavenumber vector \((k^o_x, k^o_y)\) is given by:

\[
F = \left\{ (k^n_x, k^n_y) : \sqrt{(k^n_x - k^o_x)^2 + (k^n_y - k^o_y)^2} = \delta k_{xy} \right\}, \tag{2.8}
\]

In order to find all \((k^n_x, k^n_y)\) from (2.8), we note that this is an equation of a circle with center \((k^o_x, k^o_y)\). Hence, wavenumber vectors \((k^n_x, k^n_y)\) are given by:

\[
k^n_x = k^o_x + \delta k_{xy} \cos \alpha \\
k^n_y = k^o_y + \delta k_{xy} \sin \alpha
\tag{2.9}
\]

where, \( \alpha \in [0 : 2\pi] \). Solving the above two equations simultaneously, we get the desired set \( G \) of all the azimuth \((\theta_n)\) and elevation \((\phi_n)\) angles just resolvable from the incident bearing of \((\theta_o, \phi_o)\), given by:

\[
G = \left\{ (\theta_n, \phi_n) : \theta_n = \tan^{-1} \left( \frac{k^n_x}{k^n_y} \right), \phi_n = \sin^{-1} \left( \frac{k^n_x - k^o_x}{|k||\sin \theta_n - \cos \theta_n|} \right) \right\}. \tag{2.10}
\]

After calculating the elements of the set \( G \), we can map them to the set \( H \) of actual \( x \) and \( y \)-coordinates on the cell, using:

\[
H = \left\{ (x_t, y_t) : y_t = \frac{z \tan \phi_n}{\sqrt{1 + \tan^2 \theta_n}}, x_t = y_t \tan \theta_n \right\}. \tag{2.11}
\]

The significance of the above resolvability criteria in our ability to separate users is that, if another planewave is incident with bearings \((\theta_2, \phi_2) \notin G\), we will be able
to differentiate it as a separate planewave from \((\theta_o, \phi_o)\). So, in order to quantify the average performance of our proposed system with a finite aperture circular antenna, we find the Rayleigh region around all the elements of set \(D_a\), take their convex hull and map it back to the ground using the reverse mapping given in (2.11).

**Collision events**

The collision event is defined as when at least two users pick the same code and, either (i) they have overlapping angle-of-arrivals at the base-station due to overlap in one-rings on the ground (e.g. Figure 2.1), or, (ii) even if there is no overlap in user’s one-ring, the antenna resolution at the base-station is not sufficient to classify the two incident planewaves as belonging to two different users (e.g. Figure 2.2). The following procedure outlines the numerical computations for calculating \(P_{b,R}\) for a finite aperture antenna, i.e., \(R < \infty\).

(i) As an example, consider a user to be at location \((g, h) \in \mathbb{R}^2\) in the cell with a one-ring radius of \(r\).

(ii) The angular spread in users’s signal angle-of-arrival at base-station will be confined to an egg-shaped set \(D_a\), described by (2.6).

(iii) Compute the region around every element of the set \(D_a\) satisfying the Rayleigh criterion, given by (2.10).

(iv) Map the convex hull back to their respective locations on the ground, by (2.11). That is, from the angles \((\theta, \phi)\), calculate the locations \((x, y)\) on the ground.

(v) In addition, we also need to take care of the fact that each user has a spread in its signal as captured by one-ring model. Hence, in order to have no collision, the users coming from a PPP with mean \(\rho A\) further need to be apart from the points specified by the convex-hull-mapped-back-to-ground by distance \(r\).
We generalize the above procedure to \( \rho A \) users arriving according to 2-D PPP in the cell. We numerically calculate this area and use it to simulate the \( P_{b,R} \) of our proposed system with finite aperture antenna. Further details of our numerical analysis are given in the next section.

2.3 Results of Numerical Evaluation

In this section, we compare the performance of our proposed method with the baseline method. For the sake of simplicity, we choose a rectangle-dimension plane, with the base-station at its center, hence we choose \( x \)-axis \( \in [-500,500] \) m and \( y \)-axis \( \in [0,500] \) m. The height of the base-station \( z \) is fixed to 25m, the frequency of transmission is 2.3GHz and the number of orthogonal codes \( L \) being used are 64 (following current LTE standards).

**Small antenna radius:** To study the performance of our proposed system, we choose antenna radius \( R = 0.5 \)m and study the impact of the one-ring model radii \( r = \{1,5\} \)m. Fig. 2.4 shows the simulated probability of collision of our proposed system versus the baseline system as the number of users in the plane is increased. As shown in Fig. 2.4, that even with large one-ring radius of \( r = 5 \)m, with an average number of 4 users when the probability of collision in the baseline system is nearly 50\%, the probability of collision in our proposed system is only 10\%, 5\times lower than the baseline. Moreover, as we move to 25 users, the probability of collision in the baseline system is nearly 98\%, whereas the probability of collision in our proposed system is only 38\%, nearly 2.5\times lower.

**Large antenna radius:** We emulate large antennas with a radius of \( R = 2 \)m and use the same one-ring model radii \( r = \{1,5\} \)m for all systems. Fig. 2.5 shows the effect of increasing one-ring model radius on collision probability. From Fig. 2.5,
we notice that with large antennas radius, the probability of collision is lowered even further. For example, even with large one-ring radius of $r = 5\text{m}$, we see that for an average number of 10 users when the probability of collision in the baseline system is nearly 50%, the probability of collision in our proposed system is only 4%, $12.5 \times$ lower than the baseline. Moreover, as we move to 25 users, the probability of collision in the baseline system is nearly 98%, whereas the probability of collision in our proposed system is only 15%, nearly $6.5 \times$ lower.

Figure 2.4: Probability of collision comparison between baseline and proposed scheme with small antenna radius, $R = 0.5\text{m}$. 
Figure 2.5: Probability of collision comparison between the baseline and proposed scheme with large antenna radius, $R = 2\text{m}$. 
Chapter 3

Performance Evaluation for Drone-to-Base Station Channels

In this chapter, we first study the salient characteristics of drone-to-base station channels in Section 3.1. Then, inspired by these channel models, in Section 3.2 we propose a simple clustering algorithm to help in the identification of two or more drones using the same code during the random access process. Finally, in section 3.3 we study the effect of augmenting spatial dimension with code dimension to improve the efficiency of random access process in drone-to-base station channels.

3.1 Characteristics of Drone-to-Base Station Channels

Air-to-base station channels are uniquely different from ground-to-base station channels, as they have a higher likelihood of being line-of-sight, with limited to no multipath [27]. Consider the scenario in which the base-station is mounted at an elevation, a typical height would be $h_{bs} = 25m$ and the drone is flying above the ground at a height $h_{dr} = 50m$. Then, in this case, we have the following two sources of fading:

**Large scale fading:** In most of the scenarios, due to a direct line-of-sight path between the drones and the base-station, large scale fading is usually modelled as free-space pathloss (PL). In certain scenarios, the large scale fading is also modelled as the well-known two-ray model due to the presence of a strong multipath reflection from earth’s surface. However, the multipath component due to earth’s reflection may not always be present as it depends on the reflective properties of the ground surface.
or can be very small due to sufficient height of drone from the ground and, moreover, can also be suppressed via directional antennas. The large scale fading results of various measurement campaigns in literature in different scenarios are summarized in Table 3.1.

**Small scale fading:** Small scale multipath components, if present, are usually modelled as Rician due to the presence of a strong line-of-sight component. Small scale fading can arise from the ground scatterers, if the drone is flying too low, or if it is flying near a tall building and from the air-frame of the drone itself. Increasing the height of the drone and careful placement of antennas on the drone body usually results in decreased effect of small scale multipath components. The small scale fading results of various measurement campaigns in literature in different scenarios are summarized in Table 3.2.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Channel Model</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>urban, sub-urban, rural</td>
<td>free-space PL</td>
<td>[28]</td>
</tr>
<tr>
<td>urban</td>
<td>free-space PL</td>
<td>[29]</td>
</tr>
<tr>
<td>urban, sub-urban</td>
<td>modified free-space PL</td>
<td>[30]</td>
</tr>
<tr>
<td>urban, sub-urban</td>
<td>two-ray model</td>
<td>[31]</td>
</tr>
<tr>
<td>urban</td>
<td>log-distance PL</td>
<td>[32]</td>
</tr>
<tr>
<td>urban, open field</td>
<td>log distance PL</td>
<td>[33]</td>
</tr>
</tbody>
</table>

Table 3.1: Large scale fading in drone-to-base station channels.
<table>
<thead>
<tr>
<th>Scenario</th>
<th>Channel Model</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>urban, sub-urban</td>
<td>Ricean</td>
<td>[31]</td>
</tr>
<tr>
<td>urban, sub-urban</td>
<td>Ricean</td>
<td>[34]</td>
</tr>
<tr>
<td>urban, sub-urban</td>
<td>Ricean</td>
<td>[35]</td>
</tr>
<tr>
<td>sea/fresh water</td>
<td>Ricean</td>
<td>[36]</td>
</tr>
<tr>
<td>forest/foliage</td>
<td>Ricean/Nakagami</td>
<td>[37]</td>
</tr>
</tbody>
</table>

Table 3.2: Small scale fading in drone-to-base-station channels.

3.2 Drone-to-Base Station Channels: Proposed Clustering Algorithm

Due to the channel characteristics detailed in Section 3.1, we model the channel between drones and base-station as free-space path loss. We let four drones transmit using the same random access code and concurrently at azimuth angles $\theta = \{50^\circ, 80^\circ, 110^\circ, 140^\circ\}$ and elevation angle $\phi = \{120^\circ\}$. Next, we use MUSIC algorithm [7] with 3x3 spatial smoothing [9] to plot power-angle spectrum of the received signal at the base-station. Power-angle spectrum is the plot of power versus angles received at the base-station, as shown in Fig. 3.1. Due to the line-of-sight nature of the channel and sufficient angular separation between drones, we see four distinct peaks belonging to four different drones. Hence, we argue that this capability of massive MIMO base-stations to find the direction the signal is coming from and the unique line-of-sight drone-to-base station channel characteristics, provide us with a this new opportunity to exploit the spatial dimension as a means to resolve collisions. There-
fore, provided we have sufficient angular separation, we can distinguish between four
different drones even if they used the same code and, hence, improve the efficiency of
random access and in return decrease latency in connecting users to the base-station.

Figure 3.1: MUSIC angle-of-arrival estimation of four drones transmitting at $\theta = \{50^\circ, 80^\circ, 110^\circ, 140^\circ\}$.

### 3.3 Probability of Collision with Random Drone Placement

For simulations, as shown in Fig. 3.2, we choose a rectangle-dimension plane, with
parameters $x$-axis $\in [-500, 500]$ m and $y$-axis $\in [0, 500]$ m, and with the base-station
at its center. The height of the drones $h_{dr} = 50$ m above the ground, the frequency
of transmission is 2.3GHz and the number of orthogonal codes $L$ being used are 64
(following current LTE standards).

We evaluate the performance of our proposed scheme utilizing spatial dimension
to resolve collisions under two settings: first, when the drones have power control;
this means that each drone transmits with a power that compensates for its path loss, therefore, every drone’s receive signal power at the base-station is the same. Second, we simulate the effect of no power control, which means that each of the drones will be transmitting at different powers with respect to each other, and hence, their signals will not be received with equal power at the base-station. Hence, when drones have no power control, they randomly chooses a transmit power from a set of \{2, 4, 6, 8, 10, 12, 14, 16, 18, 20\} dB.

In Fig. 3.3, we show the comparison of a random access system with transmit power control and the one without transmit power control versus the baseline system. We gradually increase the number of users in the plane and plot the probability of collision. By comparing collision probability curve of no transmit power control against the baseline collision probability, we see that the performance of our system
without power control is nearly the same as that of the baseline system. i.e. we see that for an average number of 10 users when the probability of collision in the baseline system is nearly 50%, the probability of collision in our proposed system is 42%, only $1.2 \times$ lower than the baseline. Moreover, as we move to 25 users, the probability of collision in the baseline system is nearly 98%, whereas the probability of collision in our proposed system is 89%, only $1.1 \times$ lower. However, with transmit power control, we see that for an average number of 10 users when the probability of collision in the baseline system is nearly 50%, the probability of collision in our proposed system is only 14%, $3.5 \times$ lower than the baseline. Moreover, as we move to 25 users, the probability of collision in the baseline system is nearly 98%, whereas the probability of collision in our proposed system is 58%, nearly $1.7 \times$ lower. This shows that without power control spatial dimension doesn’t contribute significantly in reducing the collision probability.

Figure 3.3: Probability of collision versus average number of drones in the plane.
Reason for drastically reduced performance of unequal transmit power case: In order to find the reason for drastically reduced performance of unequal transmit power case, we look at the power-angle spectra of the equal and unequal power cases. Fig. 3.4a shows the power-angle spectrum of four drones with equal transmit powers whereas Fig. 3.4b shows the power-angle spectrum when the four drones have unequal randomly selected powers. We see that in unequal power case the signal of the strongest user overwhelms the net reception from all the users.
Figure 3.4: Power-Angle Spectrum (PAS): equal versus unequal powers.

(a) PAS of users with equal receive powers

(b) PAS of users with unequal receive powers
Chapter 4

Performance Evaluation for Ground-to-Base Station Channels

In this chapter, we first discuss the important large scale and small scale parameters of ground-to-base station channels obtained from LTE’s 3GPP channel model standard in Section 4.1. Then, we present a simple multipath clustering and user-identification algorithm based on our studies on LTE’s 3GPP channel model in Section 4.2. Finally, in section 4.3, we study the effect of supplementing spatial dimension with code dimension in decreasing the collision probability of random access process in ground-to-base station channels.

4.1 Characteristics of Ground-to-Base Station Channels

Ground-to-base station channel is highly dispersive due to the presence of large number of scatterers, as shown in Fig. 4.1. To model the propagation environment for ground-to-base station channels, we generate the large scale and the small scale parameters from LTE’s 3GPP channel model, as explained below:

Large scale parameters:

Let’s say there are $T$ users present in the cell at coordinates $(x_t, y_t)$ where $t = 1, ..., T$, transmitting concurrently to the base-station, then we first generate their correlated large scale parameters. These seven large scale parameters are Delay Spread (DS), Azimuth Spread of Arrival (ASA), Azimuth Spread of Departure (ASD), Zenith Spread of Arrival (ZSA), Zenith Spread of Departure (ZSD), Ricean K factor (K)
and Shadow Fading (SF). To generate correlations between large scale parameters of $T$ number of users, based on user locations $(x_t, y_t)$ where $t = 1, ..., T$, we sample the whole cell at uniformly spaced intervals. Each point in this grid is assigned seven Gaussian IID zero-mean and unit variance random numbers, one corresponding to each large scale parameter. Next each parameter surface is filtered in a two-dimensional grid [38] by using empirically determined parameter values from [1]. After this filtering, only the large scale parameters corresponding to $T$ user locations are saved and the rest of the points in the two-dimensional grid are discarded. However, the values of now-correlated large scale parameters are still Gaussian distributed with zero mean and unit variance as well as are on decibel scale. So, first we convert them to linear scale from decibel scale. After that, we scale them with desired mean and variances of the large scale parameters (we mention relevant specific values in Section 4.2) and finally convert them from Gaussian to lognormal distribution, as
specified by the standard [1].

**Small scale parameters:** In LTE’s 3GPP channel model, each user’s signal comprises of cluster and rays within clusters. So, next we generate cluster delays and cluster powers utilizing the DS parameter value obtained from the large scale fading. The cluster powers are normalized such that the sum of cluster powers is one. Then we generate power of rays within clusters according to Section 7.6.2 of [1] for large antenna arrays. Next, using ASA and ZSA parameters values from large scale fading, azimuth and elevation angles are generated first for all the clusters and then for all the rays within each cluster, using cluster azimuth spread of arrival $c_{ASA}$ and cluster zenith spread of arrival $c_{ZSA}$ parameters. Finally, after generating all the large scale and small scale parameters, the final channel coefficients are generated and applied to each user’s transmission.

### 4.2 Ground-to-Base Station Channels: Proposed Clustering Algorithm

Fig. 4.2a shows the result of generating azimuth and elevation angles for user 1 transmitting at $\theta_1 = 90^\circ$ and $\phi_1 = 76^\circ$ respectively. Similarly, Fig. 4.2b shows the result of generating azimuth and elevation angles for user 2 transmitting at $\theta_2 = 30^\circ$ and $\phi_2 = 76^\circ$ respectively. The transmission parameters are being generated according to following parameters of LTE’s 3GPP channel model [1]:

- Number of clusters = $G = 12$
- Number of rays within clusters = $F = 20$
- Azimuth Spread of Arrival: $\mu_{ASA} = 10^\circ$ and $\sigma_{ASA} = 1.6^\circ$
• Zenith Spread of Arrival: $\mu_{ZSA} = 1.25^\circ$ and $\sigma_{ZSA} = 1.4^\circ$

• Cluster azimuth spread of arrival = $c_{ASA} = 3^\circ$

• Cluster zenith spread of arrival = $c_{ZSA} = 3^\circ$

We notice from Fig. 4.2 that most of the cluster power is confined within the range of $20^\circ$, albeit there are a few low-power angles which seep out of this range. Next, we observe the power-angle spectrum at the base-station generated by MUSIC [7] algorithm with 3x3 spatial smoothing [9] as shown in Fig. 4.3. We make following observations from this plot: firstly, contrary to the situation in drone-to-base station channel, each individual peak no longer corresponds to a different user. However, distinct peaks generated by a single user lie within $20^\circ$ of each other, as was depicted by the power versus angles histogram plot of Fig. 4.2.

**Steps of our clustering algorithm:** We summarize the our clustering algorithm, inspired by the LTE’s 3GPP channel model, below:

1. First we compute the power-angle spectrum of the net reception from all the users at the base-station.

2. Then we detect and note the peaks above a certain dynamic threshold.

3. Next, we start processing on the peaks. We pick the first peak and check how many peaks are within $20^\circ$ of it and assign them to one user. The reason for this step is that, according to LTE’s 3GPP channel model, the spread of angle-of-arrival peaks of a user is highly probable to remain within $20^\circ$. Hence, even though multiple peaks within this range may or may not belong to more than one user, in which case we have a collision, the peaks outside this range very likely to belong to another user.
4. We repeat this process until all the peaks are classified in this manner.

As an example, Fig. 4.4 shows the result of correct clustering of four users by our algorithm.

### 4.3 Probability of Collision with Random User Placement

In this section, we evaluate the performance of augmenting the code dimension with spatial dimension for user-identification in ground-to-base station communication. For simulations, we choose a rectangle-dimension plane, with the base-station at its
Figure 4.3 : Example power-angle spectrum generated by two users according to LTE’s 3GPP channel model.

Figure 4.4 : Example of correct clustering of four users.
center, with parameters x-axis \( \in [-500, 500] \) m and y-axis \( \in [0, 500] \) m. The height of the base station above the ground \( h_{bs} \) is fixed to 25m, the frequency of transmission is 2.3GHz and the number of orthogonal codes \( L \) being used are 64 (following current LTE standards). This scenario is depicted in Fig. 4.5.

![Simulation scenario for random user placement in LTE’s 3GPP channel model environment.](image)

**Figure 4.5**: Simulation scenario for random user placement in LTE’s 3GPP channel model environment.

In Fig. 4.6, we shows the comparison of our proposed random access system for user-identification versus the baseline system. We use two antenna configurations: 8x8 planar antenna array and 20x20 planar antenna array. We gradually increase the number of users in the plane and evaluate the probability of collision via monte-carlo simulations.

**Discussion on the results**: From Fig. 4.6, we see that for a 20x20 antenna array, with an average number of 10 users when the probability of collision in the baseline system is nearly 50%, the probability of collision in our proposed system is only 21%,
2.3× lower than the baseline. Moreover, as we move to 25 users, the probability of collision in the baseline system is nearly 98%, whereas the probability of collision in our proposed system is 70%, nearly 1.4× lower. It seems that the proposed clustering algorithm is not very robust for ground-to-base station channels. We believe that this is due to the fact that the angle-of-arrivals are only probabilistically bounded and can seep out of their 20° range and can effect the performance our clustering algorithm. However, we believe that this collision probability can be further lowered by using time-of-flight information in addition to the angle-of-arrival information for classifying the peaks as belonging to a specific user or not.

Figure 4.6: Probability of collision versus average number of users on the ground.
Chapter 5

Conclusion

An efficient and timely connection of a large number of devices is still an open problem for future 5G networks. To improve the efficiency of random access and to decrease the latency in connecting users to the base-station, in this thesis we proposed to augment code dimension with spatial dimension for collision resolution.

First, we presented a signal-space based analysis to quantify potential reduction in random access collision probability as a function of the array aperture dimension and scattering in the channel. We analytically showed that even in the high-scattering environments significant reduction in random access collision probability is possible using appropriately large arrays, a characteristic of the future 5G networks. With the proposed concept of using angle-domain separability, we analytically showed that there is a potential to reduce the latency in random access significantly, which is a key design metric for 5G systems.

Secondly, we showed that angle-of-arrival domain localized line-of-sight drone-to-base station channel provides us with the unique opportunity to utilize spatial dimension to resolve collisions in drone-to-base station channels. Even if more than one drones use the same code to access the base-station, due to the non-dispersive nature of the channel, we can conclude with high confidence that each distinct peaks on the power-angle spectrum provided by MUSIC algorithm at the base-station signifies an individual drone. This insight helps us in identifying users despite small
angle-of-arrival differences.

Thirdly, we study the ground-to-base station channel with the help of LTE’s 3GPP channel model. We find out that in this case, each distinct peak on the MUSIC power-angle spectrum computed at base-station does not correspond to an individual user. However taking insights from the power versus angle histogram plot of the users using LTE’s 3GPP channel model, we find out the the angle-of-arrival are probabilistically bounded. We use this insight to aid our simple clustering algorithm which in turn helps in reducing collisions in a highly multipath rich environment of ground-to-base station channels.

Finally, in our ongoing work, we are combining the collision resolution gains from both channels, air-to-base station and ground-to-base station, to create a comprehensive system. Moreover, for even improved collision resolution, we plan to use time-of-arrival information in addition to angle-of-arrival information as an input to our clustering algorithm. Finally, we plan to prototype and analyze experimentally collected data in various propagation environments using massive MIMO base-stations installed at Rice University campus.
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