Hierarchical Codebook Design For IRS Assisted Angular Estimation of User Position

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Under the Supervision of Dr. Gourab Ghatak

Indraprastha Institute of Information Technology Delhi
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Certificate

This is to certify that the thesis titled "**Hierarchical Codebook Design For IRS Assisted Angular Estimation of User Position**" being submitted by **Vaibhav Bhat** to the Indraprastha Institute of Information Technology Delhi, for the award of the Master of Technology, is an original research work carried out by him under my supervision. In my opinion, the thesis has reached the standards fulfilling the requirements of the regulations relating to the degree.

The results contained in this thesis have not been submitted in part or full to any other university or institute for the award of any degree/diploma.

December, 2021

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Abstract

With the increase in demand for high-speed connectivity, millimeter-wave (mmwave) communication has received increasing attention from academia and industry due to its exceptional advantages. Compared to existing wireless communication techniques, such as Wi-Fi and 4G, mmwave communications operate at higher carrier frequencies and thus come with benefits including massive bandwidth, narrow beam, high transmission quality, and strong detection ability. Furthermore, highly directional nature of mmwave help in localization of users in the network. On other hand, due to its high frequency, mmwaves are highly susceptible to attenuation and blockages. Consequently, if the user is at a great distance from the source, then due to high atmospheric attenuation, that user is out of coverage. To deal with such scenarios, we have proposed a system which employs Intelligent Reflecting Surfaces (IRS), that helps in angular estimation of the positions of users that are far away from the Base Station(BS). Thus, it helps in estimating positions of users with higher accuracy and provides better localization in a cellular network. Furthermore, we have proposed a hierarchical codebook approach to estimate angular positions of users, and we compared it with tradition methods like exhaustive search, showing how the proposed method is computationally more efficient. And, we have used Cramer Rao Lower Bound (CRLB) to observe the degradation of angular estimation performance as distance between IRS and users increase. We also used it to demonstrate improvement in angular estimation performance by increasing number of IRS elements. We found that IRS assisted system provides much better angular estimation of users positions than a system with only a BS. Furthermore, we also found that Hierarchical codebook method is more computationally efficient than traditional methods like exhaustive search.

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Chapter 1

Introduction

High speed communication demands the utilization of high frequency spectrum. This has lead to increase in popularity of millimter wave (mmwave) communication. mmwaves provide very high data rate and high bandwidth. On the other hand, the signals in this spectrum are highly susceptible to free space path loss. This in turn limits the distance over which mmwaves can be employed.

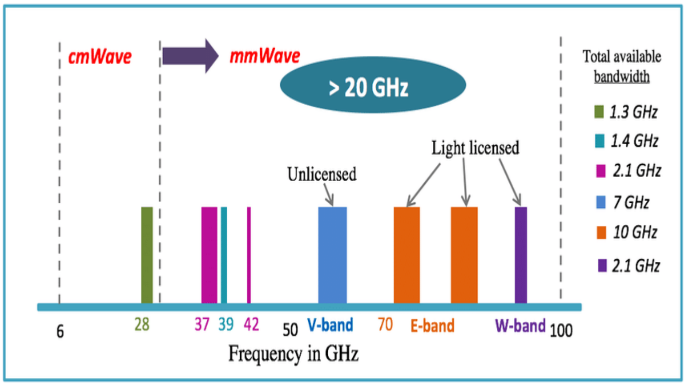

Figure 1.1: mmwave Spectrum [1]

In order to provide high speed connections, the position of the user relative to the transmitter plays a very important role. Currently, many user position estmation algorithms are employed for lower frequency bands (2.4 GHz and 5 Ghz) [2] but this topic is still in its infancy when it comes to mmwaves. Localization algorithms can be broadly categorized into three categories, proximity, scene analysis and geometry based [2]. Proximity based approaches estimate proximity of a user to an anchor point [2]. Scene analysis methods use a pre-surveyed set of signal features from different locations and compare them with signal features sampled at the user to estimate the user's position [2]. Geometry based approach use geometrical correlation between user and transmitter to estimate its position [2].

One of the potential solutions to tackle the problem of high attenuation, in case of mmwaves, is to use Intelligent Reflecting Surface (IRS). By strategically placing IRS in the environment, the range of mmwave communication can be increased and position estimation for far away users can be performed.

1.1 mmwave Communication

mmwave communication refers to the communication that utilizes the frequencies in range from 28 GHz to 300 GHz. These waves provide high speed communication owing to their high frequencies. mmwave helps facilitate high data rate services like IoT, Remote access [3]. To support such high data rates, mmwave communication systems should have low latency, mobility support etc [3]. Even though these waves provide high data rates, because of their high frequencies, they suffer heavily from atmospheric attenuation and blockages. To remedy these issues, various technologies are being developed. One such technology is the use of IRS.

1.2 Intelligent Reflecting Surface

IRS consists of an array of reflective elements. These elements do not introduce any amplitude or frequency changes on the incoming signals. They only introduce phase changes by directing the incoming signal in the desired direction. Thus, IRS facilitate the communication between a transmitter and a receiver if the quality of communication is poor. IRSs have been gaining a lot popularity in the wireless communication fraternity. Just by placing them at appropriate positions, network performance can be improved. But, in order to do that, the channel between the IRS and the user needs to be determined. [4] proposed a joint communication and localization approach using adaptive beamforming by considering just one IRS and user in the system. [5] discussed a method to perform channel estimation by using single value decomposition (SVD), which, instead of taking cascaded channel between Tx-IRS and IRS-Rx, estimates these two channels separately. Along the same lines, [6] discussed a different method of channel estimation for IRS assisted system. The method called Atomic Norm Minimization was used that performs super-resolution estimation of channel parameters. mmwave communication promises high speed data rates, but due to high attenuation, this is very difficult to achieve. In order to tackle such issues, [7] discussed a joint beamforming algorithm for IRS using channel state information. The aim was to optimize the IRS elements in order to maximize the ergodic rate of the system. The problem of channel estimation becomes more complicated if the users are continuously moving. [8] discussed such a scenario, in which a continuous time system was developed. It showed how performance can be maximized without adding Doppler spread for mobile users.

As we can see, most of the work on deployment of IRS, pertains to providing high speed communication at the users. Furthermore, localization using IRS mostly considers the localization performance of IRS with respect to a single user. Hence, we have proposed a system that helps in angular estimation of multiple users positions in a network at the same time. And we have further modified our system to group users into smaller clusters and observed how placing an IRS for each cluster improves angular estimation performance.

Chapter 2

Experimental Setup

In this section we will describe the system setup along with the codebook method utilized for angular estimation of user's position.

2.1 System Model

We have considered a circular cell with users uniformly distributed in the cell. The BS is located at the origin, i.e., [b_x,b_y] = [0,0], and IRS is located at [r_x,r_y] to facilitate angular estimation of user equipment(UE) position [m_x,m_y]. Multiple such IRSs are there inside the cell. We have further divided the cell into M rings of equal thickness. In each ring 'N' users are uniformly distributed. We have used K-means clustering algorithm to group users in each ring. At the BS and UEs, a Uniform Linear Array (ULA) is considered with N_b and N_m antennas respectively. All the IRSs have N_r elements. To reduce the complexity of the system all UE antennas are connected to a single RF chain each. The distance between two elements is d = λ/2, where λ is the wavelength. Free space path model is considered between Tx and Rx.

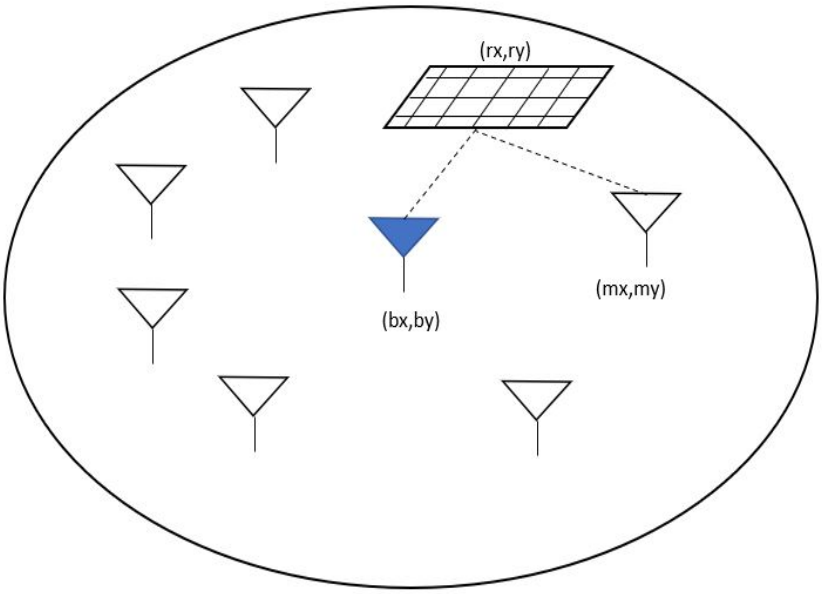

Figure 2.1: System setup

$$h = \lambda/(4\pi r^2). \tag{1}$$

And for path loss in BS-IRS-UE channel we use the expression given in [9],

$$h = \left(\frac{C}{4\pi r_1 r_2}\right)^2, \tag{2}$$

where

$$C = N_{\mathrm{r}}(\lambda/2)^2. \tag{3}$$

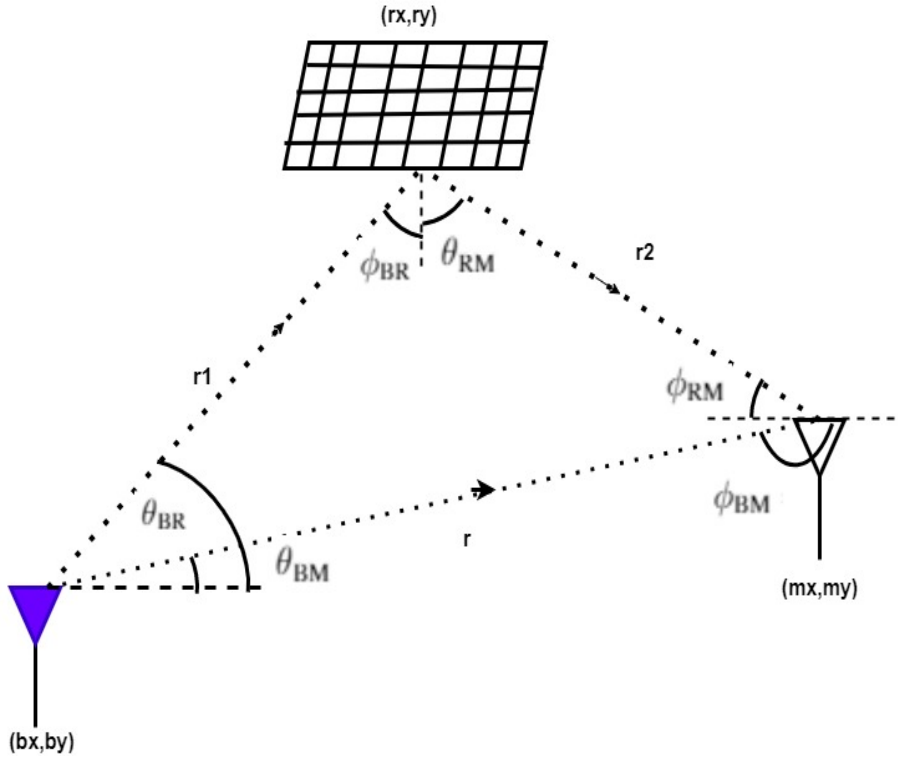

Figure 2.2: BS-UE communication via IRS

2.2 Channel Model

Since mmwave is spatially sparse [10], a single path communication is considered between BS and users. The received signal at a user *k* is given as

$$y_k = h_k^H w_k \sqrt{P_t} s_k + n_k, \tag{4}$$

where h_k and w_k are channel and beamforming vectors respectively, P_t is the transmitted power, s_k is the transmitted symbol and n_k is the additive noise.

The combined channel from BS to UE through IRS is given by

$$H = H_{\mathrm{BM}} + H_{\mathrm{RM}} \Theta H_{\mathrm{BR}}, \tag{5}$$

where $H_{\mathrm{BM}} \in \mathbb{C}^{\mathrm{N_m x N_b}}$ denotes the direct channel from BS to UE and $H_{\mathrm{BR}} \in \mathbb{C}^{\mathrm{N_r x N_b}}$, $H_{\mathrm{RM}} \in \mathbb{C}^{\mathrm{N_m x N_r}}$ are channels from BS to IRS and from IRS to UE respectively. Here $\Theta \in \mathbb{C}^{\mathrm{N_r x N_r}}$ is the phase shift matrix given by $\Theta = \beta diag(\, e^{j\varphi_1}\ e^{j\varphi_2} \ldots\ldots\ e^{j\varphi_{\mathrm{N_r}}})$ and $\varphi_1, \varphi_2, ...\varphi_{\mathrm{N_r}}$ are phase shifts of each IRS element and β is the reflection coefficient [11]. Furthermore,

$$H_{\mathrm{BM}} = h_{\mathrm{BM}} a_{\mathrm{r}}(\phi_{\mathrm{BM}}) {a_{\mathrm{t}}}^{\mathrm{H}}(\theta_{\mathrm{BM}}), \tag{6}$$

$$H_{\text{RM}}\Theta H_{\text{BR}} = h_{\text{BR}}h_{\text{RM}}a_{\text{r}}(\phi_{\text{RM}})a_{\text{t}}{}^{H}(\theta_{\text{RM}})\Theta a_{\text{r}}(\phi_{\text{BR}})a_{\text{t}}{}^{H}(\theta_{\text{BR}}), \tag{7}$$

Here ϕ_{BM},θ_{BM},h_{BM} are AOA,AOD and path gain respectively from BS to UE. Similarly, ϕ_{BR},θ_{BR},h_{BR} and ϕ_{RM}, θ_{RM},h_{RM} can be interpreted accordingly.

And the values of these parameters can be formulated as

$$\theta_{\text{BM}} = tan^{\text{-1}}\left(\frac{m_{\text{y}} - b_{\text{y}}}{m_{\text{x}} - b_{\text{x}}}\right), \tag{8}$$

$$\phi_{\text{BM}} = \pi - \theta_{\text{BM}}, \tag{9}$$

$$\theta_{\text{RM}} = tan^{\text{-1}}\left(\frac{m_{\text{x}} - r_{\text{x}}}{r_{\text{y}} - m_{\text{y}}}\right), \tag{10}$$

$$\phi_{\text{RM}} = \pi/2 - \theta_{\text{RM}}. \tag{11}$$

2.3 Two Dimensional Beamforming

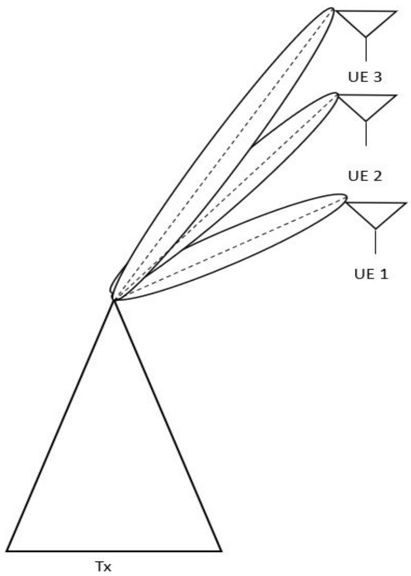

Figure 2.3: 2D Beamforming

Two dimensional beamforming is used to do beamforming along different elevation angles. 2D Beamforming is taken between BS and UEs and IRS and UEs. If user "k" is located at an angle $\bar{\theta}$ with respect to the BS, then $\bar{\theta}$ is called as the Angle of Departure (AOD). And the array response vector for N element ULA is denoted as

$$a(\theta, N) = [1\ e^{-j\pi\theta}\ e^{-j\pi 2\theta}\ ....\ e^{-j\pi(N-1)\theta}]^T, \tag{12}$$

with

$$\theta = \sin\bar{\theta}. \tag{13}$$

The channel response vector along this direction is given as

$$h = La(\theta, N), \tag{14}$$

L denotes the path loss as given in (1),(2). Channel response vector does not contain a $\sum$ as we are considering only a single path, i.e., LOS path, between BS and a user.

Beamforming is done along the channel vector [12], which means beamforming vector is given as

$$w = a(\theta, N)/\sqrt{N}, \tag{15}$$

with

$$|[w]_n| = 1/\sqrt{N}, n = 1, 2, .., N. \tag{16}$$

2.4 Codebook Design

The codebook is taken as in [13], given by

$$A(Q, N) = [a(-1 + 1/Q)\ a(-1 + 3/Q)\ ....\ a(-1 + (2Q - 1)/Q)]. \tag{17}$$

Here, Q is the number of quantization levels and $-1 + 1/Q$, ..., $-1 + (2Q - 1)/Q$ are values of $sin(\bar{\theta})$ in (13). Higher the number of quantization levels, more number of beams are available. This means that each column of A represents a beam in a particular direction. Also, θ∈[-1,1], i.e. from (13), $\bar{\theta}$∈$[-\pi/2, \pi/2]$.

For a user *k*, a beam *a(.)* is selected from A. The *a(.)* that lies closest along the AOD of the user *k* is the one that is selected. And beamforming vector is given by (15).

As we move towards higher resolution codebooks, the number of beams increase. Resolution is increased by taking higher quantization levels.

2.5 MUSIC Algorithm

MUSIC algorithm is used to get an of direction of arrival(DOA). The algorithm receives a vector of the angles of all incoming waves and then estimates the DOA based on them for each incoming beam. If there are k incoming signals at a receiver with N_{rec} antennas then received signal is given as

$$x = As + n, \tag{18}$$

with

$$A = [a(\varphi_1), ..., a(\varphi_{\mathrm{k}})] \tag{19}$$

Here, $s \in \mathbb{C}_{\mathrm{kxT}}$ is the transmitted pilot symbol, $A \in \mathbb{C}_{\mathrm{N_{rec}xk}}$ is the steering matrix. Autocorrelation matrix of *x* is given by R_x, T are the number of time samples. First *k* sorted eigen vectors of R_x span the signal subspace denoted as V_s.

Furthermore, the remaining *(N_{rec}-k)* eigen vectors correspond to the noise subspace denoted as V_n [14]. Any vector *e* in signal subspace is orthogonal to any vector in noise subspace.

MUSIC defines squared norm as given in [14],

$$d^2 = ||V_{\mathrm{N}}{}^{\mathrm{H}} e||^2 = e^{\mathrm{H}} V_{\mathrm{N}} V_{\mathrm{N}}{}^{\mathrm{H}} e, \tag{20}$$

For any *e* in $\mathrm{V_s}$, the squared norm is close to zero. Taking its reciprocal gives sharp peaks at signal frequencies.

The signal estimation function for MUSIC is given as

$$\hat{P}_{\mathrm{MU}}(e^{\mathrm{jw}}) = \frac{1}{e^{\mathrm{H}} V_{\mathrm{N}} V_{\mathrm{N}}{}^{\mathrm{H}} e}. \tag{21}$$

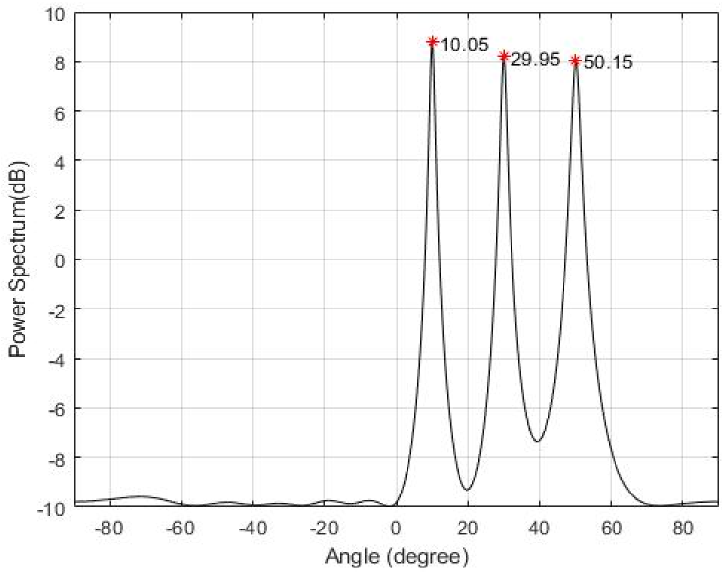

Figure 2.4: DOA Estimation using MUSIC for $\varphi = [10^{\mathrm{o}}, 30^{\mathrm{o}}, 50^{\mathrm{o}}]$

The *k* angles at which peaks occurs are DOAs of the *k* signals.

2.6 CRLB Analysis

In this section we derive the CRLB of the coordinates of UE given by ξ = [$\mathrm{m_x}$ $\mathrm{m_y}$]. The unknown channel parameters are given by η = [θ_{BM},ϕ_{BM},h_{BM},ϕ_{RM}]. To find the CRLB we first need to find the Fischer information Matrix (FIM) of η, given by, I = $C(\eta_{\mathrm{i}}, \eta_{\mathrm{j}}) = \frac{P}{\sigma^2} \mathfrak{Re}(\frac{\partial \mu^H}{\partial \eta_{\mathrm{i}}} \frac{\partial \mu}{\partial \eta_{\mathrm{j}}})$, where μ = $\sqrt{P}$Hwx [15]. We take

$$K = a_{\mathrm{t}}{}^{\mathrm{H}}(\theta_{\mathrm{RM}}) \Theta a_{\mathrm{r}}(\phi_{\mathrm{BR}}) a_{\mathrm{t}}{}^{\mathrm{H}}(\theta_{\mathrm{BR}}) wx, \tag{22}$$

When

$$\varphi_{\mathrm{i}} = \pi(i-1)[sin(\theta_{\mathrm{RM}}) - sin(\phi_{\mathrm{BR}})], \tag{23}$$

then as given in [15]

$$a_{\mathrm{t}}{}^{\mathrm{H}}(\theta_{\mathrm{RM}})\Theta a_{\mathrm{r}}(\phi_{\mathrm{BR}}) = N_{\mathrm{r}} \tag{24}$$

Hence,

$$|K| = N_{\mathrm{r}}|a_{\mathrm{t}}{}^{\mathrm{H}}(\theta_{\mathrm{BR}})wx|. \tag{25}$$

Furthermore, the free space path loss h_{BM} between BS and UE can be taken as [15]

$$h_{\mathrm{BM}} = ||b-m||_2{}^{-1}. \tag{26}$$

The elements of I are given as

$$C(\theta_{\mathrm{BM}},\theta_{\mathrm{BM}}) = \frac{PN_{\mathrm{m}}h_{\mathrm{BM}}{}^2}{\sigma^2}\left\|\frac{\partial a_{\mathrm{t}}{}^{\mathrm{H}}(\theta_{\mathrm{BM}})}{\partial\theta_{\mathrm{BM}}}wx\right\|^2, \tag{27}$$

$$C(\theta_{\mathrm{BM}},\phi_{\mathrm{BM}}) = \frac{Ph_{\mathrm{BM}}{}^2}{\sigma^2}\mathfrak{Re}(x^{\mathrm{H}}w^{\mathrm{H}}\frac{\partial a_{\mathrm{t}}(\theta_{\mathrm{BM}})}{\partial\theta_{\mathrm{BM}}}a_{\mathrm{r}}{}^{\mathrm{H}}(\phi_{\mathrm{BM}})\frac{\partial a_{\mathrm{r}}(\phi_{\mathrm{BM}})}{\partial\phi_{\mathrm{BM}}}a_{\mathrm{t}}{}^{\mathrm{H}}(\theta_{\mathrm{BM}})wx), \tag{28}$$

$$C(\theta_{\mathrm{BM}},h_{\mathrm{BM}}) = \frac{PN_{\mathrm{m}}h_{\mathrm{BM}}}{\sigma^2}\mathfrak{Re}(x^{\mathrm{H}}w^{\mathrm{H}}\frac{\partial a_{\mathrm{t}}(\theta_{\mathrm{BM}})}{\partial\theta_{\mathrm{BM}}}a_{\mathrm{t}}{}^{\mathrm{H}}(\theta_{\mathrm{BM}})wx), \tag{29}$$

$$C(\theta_{\mathrm{BM}},\phi_{\mathrm{RM}}) = \frac{Ph_{\mathrm{BM}}h_{\mathrm{BR}}h_{\mathrm{RM}}}{\sigma^2}\mathfrak{Re}(Kx^{\mathrm{H}}w^{\mathrm{H}}\frac{\partial a_{\mathrm{t}}(\theta_{\mathrm{BM}})}{\partial\theta_{\mathrm{BM}}}a_{\mathrm{r}}{}^{\mathrm{H}}(\phi_{\mathrm{BM}})\frac{\partial a_{\mathrm{r}}(\phi_{\mathrm{RM}})}{\partial\phi_{\mathrm{RM}}}), \tag{30}$$

$$C(\phi_{\mathrm{BM}},\phi_{\mathrm{BM}}) = \frac{Ph_{\mathrm{BM}}{}^2}{\sigma^2}\left\|\frac{\partial a_{\mathrm{r}}(\phi_{\mathrm{BM}})}{\partial\phi_{\mathrm{BM}}}a_{\mathrm{t}}{}^{\mathrm{H}}(\theta_{\mathrm{BM}})wx\right\|^2, \tag{31}$$

$$C(\phi_{\mathrm{BM}},h_{\mathrm{BM}}) = \frac{Ph_{\mathrm{BM}}}{\sigma^2}\mathfrak{Re}(x^{\mathrm{H}}w^{\mathrm{H}}a_{\mathrm{t}}(\theta_{\mathrm{BM}})\frac{\partial a_{\mathrm{r}}{}^{\mathrm{H}}(\phi_{\mathrm{BM}})}{\partial\phi_{\mathrm{BM}}}a_{\mathrm{r}}(\phi_{\mathrm{BM}})a_{\mathrm{t}}{}^{\mathrm{H}}(\theta_{\mathrm{BM}})wx), \tag{32}$$

$$C(\phi_{\mathrm{BM}},\phi_{\mathrm{RM}}) = \frac{Ph_{\mathrm{BM}}h_{\mathrm{BR}}h_{\mathrm{RM}}}{\sigma^2}\mathfrak{Re}(Kx^{\mathrm{H}}w^{\mathrm{H}}a_{\mathrm{t}}(\theta_{\mathrm{BM}})\frac{\partial a_{\mathrm{r}}{}^{\mathrm{H}}(\phi_{\mathrm{BM}})}{\partial\phi_{\mathrm{BM}}})\frac{\partial a_{\mathrm{r}}(\phi_{\mathrm{RM}})}{\partial\phi_{\mathrm{RM}}}), \tag{33}$$

$$C(h_{\mathrm{BM}},h_{\mathrm{BM}}) = \frac{PN_{\mathrm{m}}}{\sigma^2}\left\|a_{\mathrm{t}}{}^{\mathrm{H}}(\theta_{\mathrm{BM}})wx\right\|^2, \tag{34}$$

$$C(h_{\mathrm{BM}},\phi_{\mathrm{RM}}) = \frac{Ph_{\mathrm{BR}}h_{\mathrm{RM}}}{\sigma^2}\mathfrak{Re}(Kx^{\mathrm{H}}w^{\mathrm{H}}a_{\mathrm{t}}(\theta_{\mathrm{BM}})a_{\mathrm{r}}{}^{\mathrm{H}}(\phi_{\mathrm{BM}})\frac{\partial a_{\mathrm{r}}(\phi_{\mathrm{RM}})}{\partial\phi_{\mathrm{RM}}}), \tag{35}$$

$$C(\phi_{\mathrm{RM}},\phi_{\mathrm{RM}}) = \frac{Ph_{\mathrm{BR}}{}^2h_{\mathrm{RM}}{}^2}{\sigma^2}\left\|K\frac{\partial a_{\mathrm{r}}(\phi_{\mathrm{RM}})}{\partial\phi_{\mathrm{RM}}}\right\|^2. \tag{36}$$

Therefore,

$$I = \begin{bmatrix} C(\theta_{\text{BM}}, \theta_{\text{BM}}) & C(\theta_{\text{BM}}, \phi_{\text{BM}}) & C(\theta_{\text{BM}}, h_{\text{BM}}) & C(\theta_{\text{BM}}, \phi_{\text{RM}}) \\ C(\phi_{\text{BM}}, \theta_{\text{BM}}) & C(\phi_{\text{BM}}, \phi_{\text{BM}}) & C(\phi_{\text{BM}}, h_{\text{BM}}) & C(\phi_{\text{BM}}, \phi_{\text{RM}}) \\ C(h_{\text{BM}}, \theta_{\text{BM}}) & C(h_{\text{BM}}, \phi_{\text{BM}}) & C(h_{\text{BM}}, h_{\text{BM}}) & C(h_{\text{BM}}, \phi_{\text{RM}}) \\ C(\phi_{\text{RM}}, \theta_{\text{BM}}) & C(\phi_{\text{RM}}, \phi_{\text{BM}}) & C(\phi_{\text{RM}}, h_{\text{BM}}) & C(\phi_{\text{RM}}, \phi_{\text{RM}}) \end{bmatrix}. \tag{37}$$

The FIM of ξ is given by

$$\tilde{I} = TIT^{\text{T}}, \tag{38}$$

,where $\text{T}_{\text{ij}} = \frac{\partial \eta_{\text{i}}}{\partial \xi_{\text{j}}}$. Thus elements of T are given as

$$\frac{\partial \theta_{\text{BM}}}{\partial m_{\text{x}}} = \frac{-\sin\theta_{\text{BM}}}{||b-m||_2}, \tag{39}$$

$$\frac{\partial \theta_{\text{BM}}}{\partial m_{\text{y}}} = \frac{\cos\theta_{\text{BM}}}{||b-m||_2}, \tag{40}$$

$$\frac{\partial \phi_{\text{BM}}}{\partial m_{\text{x}}} = \frac{\sin\theta_{\text{BM}}}{||b-m||_2}, \tag{41}$$

$$\frac{\partial \phi_{\text{BM}}}{\partial m_{\text{y}}} = \frac{-\cos\theta_{\text{BM}}}{||b-m||_2}, \tag{42}$$

$$\frac{\partial \phi_{\text{RM}}}{\partial m_{\text{x}}} = \frac{-\cos\theta_{\text{RM}}}{||m-r||_2}, \tag{43}$$

$$\frac{\partial \phi_{\text{RM}}}{\partial m_{\text{y}}} = \frac{-\sin\theta_{\text{RM}}}{||m-r||_2}, \tag{44}$$

$$\frac{\partial h_{\text{BM}}}{\partial m_{\text{x}}} = -||b-m||_2{}^{\text{-2}}\cos\theta_{\text{BM}}, \tag{45}$$

$$\frac{\partial h_{\text{BM}}}{\partial m_{\text{y}}} = -||b-m||_2{}^{\text{-2}}\sin\theta_{\text{BM}}. \tag{46}$$

Thus, the CRLB of the position estimation error of a user is given by

$$\sqrt{tr(\tilde{I}^{\text{-1}})} \leq \sqrt{var(\hat{m})}, \tag{47}$$

Here var($\hat{m}$) is the variance of the position estimation given by $\text{E}[(\text{m}_{\text{x}}\text{-}\hat{m}_{\text{x}})^2] + \text{E}[(\text{m}_{\text{y}}\text{-}\hat{m}_{\text{y}})^2]$.

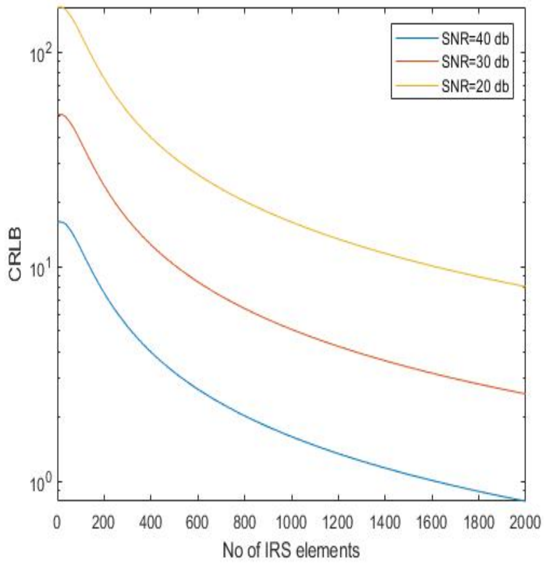

Figure 2.5: CRLB vs N_r

2.7 Effect Of Number Of IRS elements and IRS-UE Distance

To see how number of IRS elements and distance of IRS from user affects the performance, we plot CRLB against these two parameters.

To analyze effect of number of IRS elements, we take number of antennas at BS, $N_b = 500$ and number of antennas at UE, $N_m = 50$. IRS is placed at $[r_x,r_y] = [85,55]$ and UE is placed at $[m_x,m_y] = [90,50]$. And we plot it for three values of SNR, i.e., [20 30 40]dB.

From Figure 2.5, we can see that as number of IRS elements increase, the CRLB drops. Furthermore, for higher SNR, CRLB is lower. Thus, using high number of IRS elements provides better estimation of UE.

To analyze the effect of distance between IRS and UE, positions of BS and UE are taken as, $[b_x\ b_y] = [0,0]$ and $[m_x\ m_y] = [90,50]$ respectively.IRS is placed at [89,51]. Then, UE is moved away from the IRS with each iteration. $N_b = 500$ and $N_m = 50$, and it was plotted for different number of IRS elements, N_r.

We can see from figure 2.6, that as distance between user and IRS increases, CRLB starts to increase. Hence to get a good estimate of user position, IRS should be placed closer to the user. Furthermore, we can also see that for higher number of IRS elements, CRLB is lower.

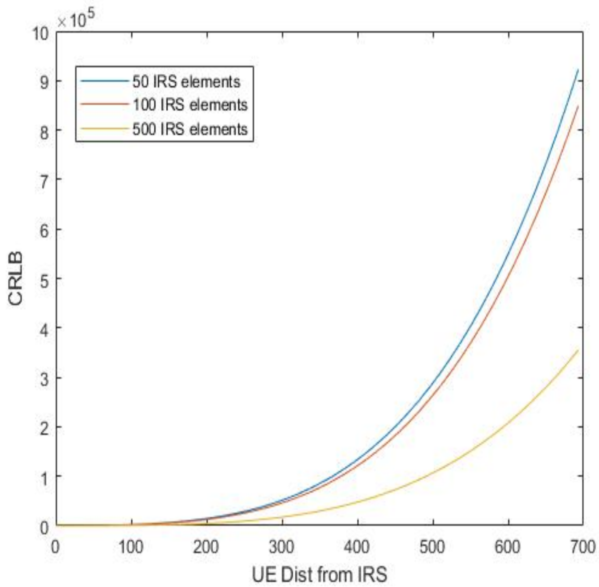

Figure 2.6: CRLB vs $d_{\text{IRS-UE}}$

Chapter 3

Proposed Algorithm

In this chapter we will present the proposed algorithm along with the hierarchical codebook estimation and MUSIC algorithm.

3.1 Angular Estimation Algorithm

We have limited our analysis to angular estimation only. If needed, RSSI can be used to obtain the distance estimation.

The analysis is done in two steps. In first step, BS is used to perform angular estimation of AOD between BS and all the users in the circular cell. A fixed resolution codebook is used at BS. The users are grouped into clusters using k-means clustering algorithm.

In next step, IRSs are used and hierarchical codebooks are employed, i.e., as we move to high order codebooks, the resolution increases. Hence, for high order codebooks we get more number of beams by taking more quantization levels.

1. For each cluster there is a dedicated IRS. IRS starts angular estimation of AOD between IRS and users in cluster 'k' with a low order codebook.
2. Then at every iteration, higher resolution codebook is used by moving up in the hierarchy till resolution threshold is reached.
3. This is done for all the clusters. Angular estimation of all the users is done simultaneously.

BS estimate is given as (x,y)

$$x = d_{\text{bs-ue}} \cos \theta_{\text{BM}} \tag{48}$$

$$y = d_{\text{bs-ue}} \sin \theta_{\text{BM}} \tag{49}$$

IRS estimate is given as (x',y')

$$x' = r_{\text{x}} + d_{\text{irs-ue}} \sin \theta_{\text{RM}} \tag{50}$$

$$y' = r_{\text{y}} \pm d_{\text{irs-ue}} \cos \theta_{\text{RM}} \tag{51}$$

Final estimated position of the user is calculated by combining the BS and IRS estimation.

$$\hat{x} = w_{\text{bs}} x + w_{\text{irs}} x', \tag{52}$$

$$\hat{y} = w_{\text{bs}} y + w_{\text{irs}} y', \tag{53}$$

here w_{bs} and w_{irs} are weights given by

$$w_{\text{bs}} = \frac{d_{\text{irs-ue}}}{(d_{\text{bs-ue}} + d_{\text{irs-ue}})}, \tag{54}$$

$$w_{\text{irs}} = \frac{d_{\text{bs-ue}}}{(d_{\text{bs-ue}} + d_{\text{irs-ue}})}, \tag{55}$$

here $d_{\text{bs-ue}}$ and $d_{\text{irs-ue}}$ are the distance of BS and IRS from a user. These weights help determine the priority of the estimate of BS and IRS based on their distance from the user.

Algorithm 1: Angular Estimation Algorithm

Input: cluster($[cl_x, cl_y]$), cluster centroid($[cen_x, cen_y]$) BS position(BS_{pos}), UE coordinates(UE_{pos}), No of IRS elements(n_{elem}), starting resolution(res_{ini}), error threshold(e_{th}), resolution threshold(res_{th})
Output: Users Positions estimate(POS_{est})
$IRS_{posx} \leftarrow cen_x$ //IRS -Positioning
$IRS_{posy} \leftarrow \max(cl_y) + 1$
$[est_{\text{ini}}, d_{\text{RM}}, DOA_{\text{est}}] \leftarrow$ IniLocAlgo(res_{ini},n_{elem},IRS_{pos},UE_{pos},BS_{pos})
$x_{est} \leftarrow IRS_{posx} + d_{\text{RM}} sin(est_{\text{ini}})$
$y_{est} \leftarrow IRS_{posy} - d_{\text{RM}} cos(est_{\text{ini}})$
$POS_{est} \leftarrow [x_{est}, y_{est}]$
$est_{final} \leftarrow est_{ini}$
while $res_{final} < res_{th}$ **do**
  [est_{final},res_{final}] $\leftarrow$ HeirarchLocAlgo(est_{final},res_{ini},DOA_{est},n_{elem})
  $x_{est} \leftarrow IRS_{posx} + d_{\text{RM}} sin(est_{\text{final}})$
  $y_{est} \leftarrow IRS_{posy} - d_{\text{RM}} cos(est_{\text{final}})$
  $POS_{est} \leftarrow [x_{est}, y_{est}]$ //Keep going till resolution crosses threshold
end
return POS_{est}

3.2 Initial Angular Estimation Algorithm

In this algorithm, MUSIC is invoked to get a rough estimate of the region where the user might be located. Then a codebook is used to find the beam that lies closest to the direction of the user.

3.3 Hierarchical Codebook Angular Estimation Algorithm

At each iteration, number of quantization levels are incremented. Thus, at each iteration, number of beams increase which lead to reduced thickness of beams which provides a tighter confidence interval. When the resolution has reached its maximum permissible value, the estimation at the end is taken as final estimate of the user's position.

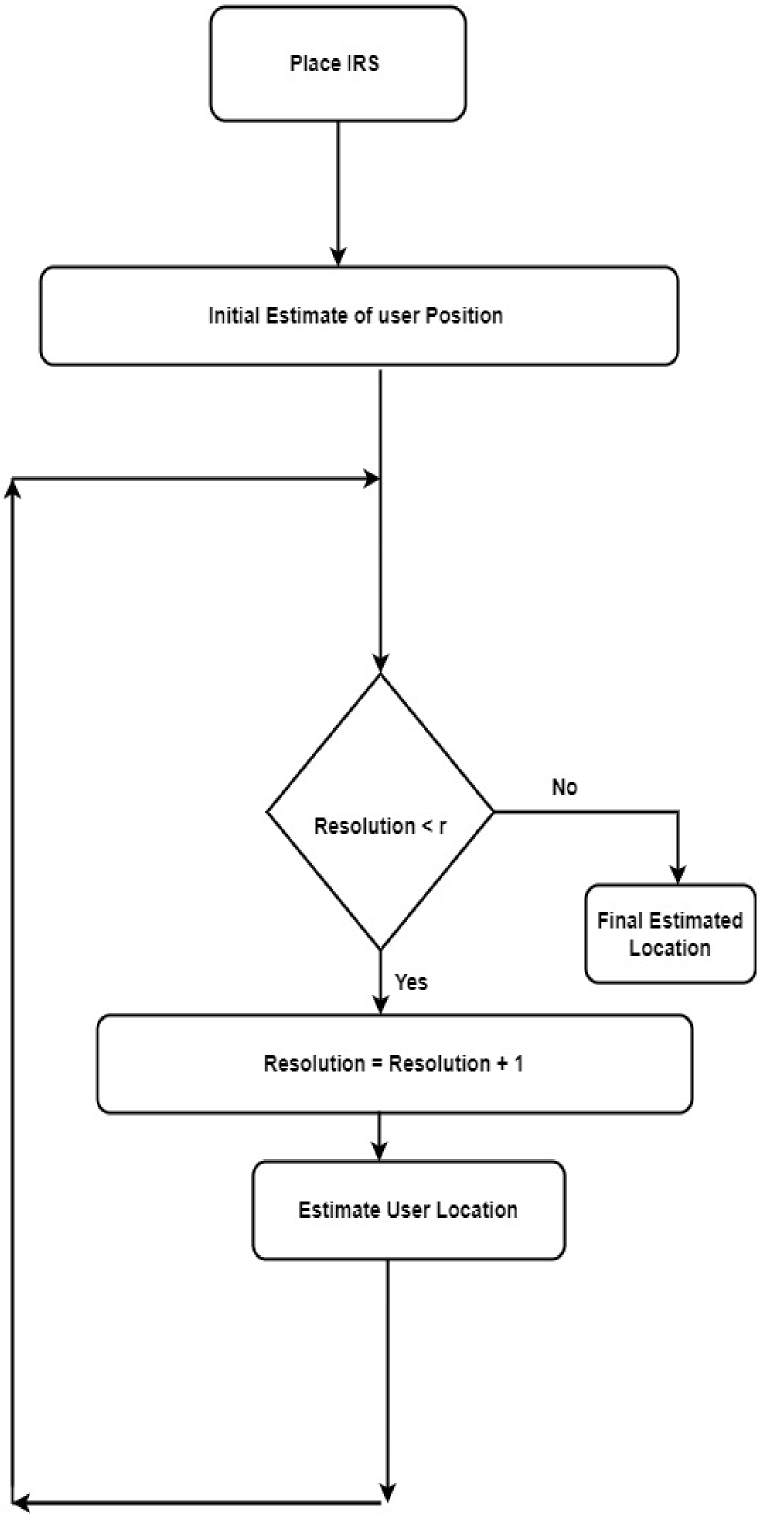

Figure 3.1: Angular Estimation Algorithm

Algorithm 2: Initial Angular Estimation Algorithm

Require: Starting resolution(res_{ini}) ,No of IRS elements(n_{elem}), IRS position (IRS_{pos}), BS position(BS_{pos}), BS-UE distance(d_{BM}),IRS-UE distance(d_{RM}),incoming signal directions(aod_{RM})

Output: Initial estimate(est_{ini})

```
DOA_est ← MUSIC(aod_RM,d_BM,d_RM,n_elem)
Theta ← -1+((2(1:res_ini)-1)/res_ini)                          //Range of angles
i=1
while i < res_ini do
    codebook(:,i)←[exp(-jπ[0:(n_elements-1)]'((Theta(i))))]  //Create Codebook
    i ← i+1
end
response ← [exp(-jπ[0:(n_elem-1)]'sin(DOA_est ))]
k=1
while k < res_ini do
    dotproduct(:,k) ← |codebook(:,k)'response|               //Check every beam
    k ← k+1
end
index ← find(dotproduct == max(dotproduct))//Beam closest along DOA_est
est_ini ← sin^-1(Theta(index))
return est_ini
```

Algorithm 3: MUSIC Algorithm

Require: Incoming beam directions(θ),n_{elem},BS-UE distance(d_{BM}),IRS-UE distance(d_{RM}), Number of time samples(T),Signal-to-Noise raito of signal(SNR).

Output: DOA_{est}

$K \leftarrow$ length(θ)
k$\leftarrow$1
while $k < K$ **do**
  A(k) $\leftarrow exp(-j\pi sin(\theta(k))(0 : n_{\text{elem}} - 1)')$
  k $\leftarrow$ k+1 //Steering Matrix
end
x $\leftarrow diag(\sqrt{(10^{(\text{SNR}/10)})/2})$
s$\leftarrow$ x(randn(K,T) + jrandn(K,T)); //Pilot Signal
noise $\leftarrow$ (randn(n_{elem},T)+jrandn(n_{elem},T))
X $\leftarrow$ A*s+noise
Rx $\leftarrow$ cov(X')
[eigenVec,eigenVal]$\leftarrow$ eig(Rx);
Vn $\leftarrow$ eigenVec(:,1:n_{elem}-K) //Noise subspace
theta $\leftarrow -\pi/2 : \pi/2$;
i$\leftarrow$1
while $i < length(theta)$ **do**
  SigSub $\leftarrow exp(-j\pi(0 : n_{\text{elem}} - 1)' * sin(theta(i)))$ //Signal subspace
  P $\leftarrow$ SigSub'*(Vn*Vn')*SigSub
  Pspec(i) $\leftarrow$ 1/ P
  i $\leftarrow$ i+1
end
Pspec $\leftarrow \mathfrak{Re}(10 * log_{10}(Pspec))$;
[pks,locs]$\leftarrow$ findpeaks(Pspec);
$DOA_{est} \leftarrow$ sort(locs(1:K));
return DOA_{est}

Algorithm 4: Hierarchical Codebook Angular Estimation Algorithm

Require: Initial estimate(est_{ini}), Starting resolution(res_{ini}) ,DOA_{est}, No of IRS elements(n_{elem}),No of neighbourhood beams(n_{neigh}).

Output: Final estimate(est_{final}), Final resolution(res_{final})

$res_{final} \leftarrow res_{ini}$+1

Theta $\leftarrow$ -1+((2(1:res_{final})-1)/res_{final}) //Range of angles

i$\leftarrow$1

while $i < length(Theta)$ **do**

  codebook(:,i)$\leftarrow$[exp(-jπ*[0:($n_{elements}$-1)]'*((Theta(i))))]

  i $\leftarrow$ i+1

end

AngleDiff $\leftarrow |est_{ini} - sin^{-1}(Theta)|$

[sortedVals,indices]$\leftarrow$ sort(AngleDiff) //Search near previous estimate

codebook $\leftarrow$ codebook(:,indices(1:n_{neigh}));

Theta = Theta(indices(1:n_{neigh}));

response $\leftarrow$ [exp(-jπ*[0:(n_{elem}-1)]'.*sin(DOA_{est}))]

k$\leftarrow$1

while $k < length(Theta)$ **do**

  dotproduct(:,k) $\leftarrow |codebook(:,k)'response|$

  k $\leftarrow$ k+1

end

index $\leftarrow$ find(dotproduct == max(dotproduct))/Beam closest along DOA_{est}

est_{final} = sin^{-1}(Theta(index))

return [est_{final},res_{final}]

Chapter 4

Simulation Results

4.1 Utility Of IRS Assisted Angular Estimation

For the simulations we have taken N_b = 500 and N_r = 100. To asses the utility of IRS assisted angular estimation, we compare it with the scenario where only BS is used to perform angular estimation for all the users in the cell. For this analysis, users are uniformly divided in a circle of radius 300 meters with BS position [b_x b_y] = [0,0]. Furthermore, users are grouped using K-means clustering and a dedicated IRS is placed for each cluster. This circular region is divided into 10 rings and each ring is 30 meter thick, given as, [20 50 80 110 140 170 200 230 260 290] with 40 users located inside each ring. And as we move towards further rings, the number of clusters increase as [2 4 6 8 10 12 14 16 18 20].

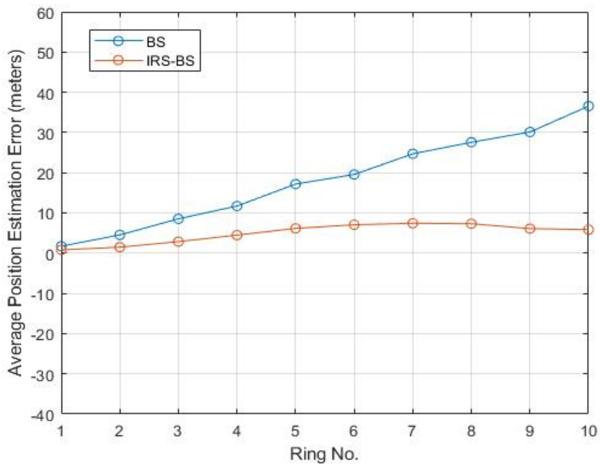

Figure 4.1: Angular Estimation Performance of BS vs BS-IRS

We can see from figure 4.1 that as we move away from BS at the center, the performance of non IRS assisted system starts to drop and position estimation error keeps on increasing. But, the IRS assisted system performs much better and the position estimation error somewhat stabilizes for far away users owing to varying cluster size.

4.2 Utility Of Hierarchical Codebooks

In order to assess the utility of hierarchical codebook, we compare it with the simple BS angular estimation that uses fixed resolution codebook. IRS is placed at [80,60] and UE is placed at [90,50] while BS is at [0,0].

We can see from the figure 4.2 that for the BS, that uses fixed resolution codebook, the position estimation error remains the same. But for hierarchical codebook,

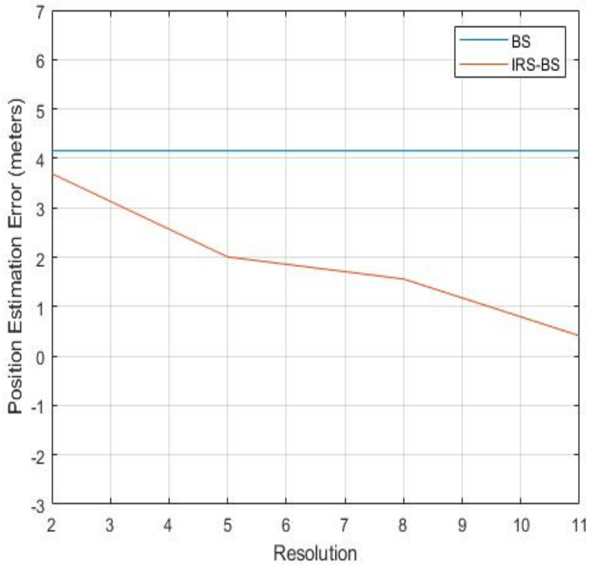

Figure 4.2: Hierarchical vs Fixed resolution codebook

as we increase the resolution, the angular estimate becomes more accurate and consequently position estimation error keeps dropping.

We also observed the effect of user distance from the IRS on the resolution of codebook. The error threshold is set equal to 1 meter and we have analyzed how long it takes for the angular estimation error to drop below this threshold for different values of distance between IRS and UE. We can see from figure 4.3 that as the distance between IRS and UE increase, it takes a higher resolution beam to achieve a good estimate.

Furthermore, to analyze the computational overhead of hierarchical codebook, we compared to Exhaustive search method.Exhaustive method check every beam available in -90 to +90 degree region, whereas, the hierarchical codebook approach only check beams in the neighbourhood of the previously estimated beam. The beam width for exhaustive search is taken as the thinnest beam width obtained from hierarchical codebook.

Table 4.1: Exhaustive Search vs Hierarchical Codebook

IRS-UE Distance	Exhaustive Search		Hierarchical Codebooks	
	No of Iterations	Estimation Error(m)	No of Iterations	Estimation Error(m)
4 m	6	0.6657	2	0.6015
11 m	12	0.8076	4	0.3274
23 m	18	1.7853	6	0.6668

In the above table we can see that hierarchical codebook provide better user position estimation and it takes fewer iterations than the exhaustive search. It can be inferred from the table that, with exhaustive search method, it would require thinner beams, i.e. more iteration to achieve comparable performance to hierarchical

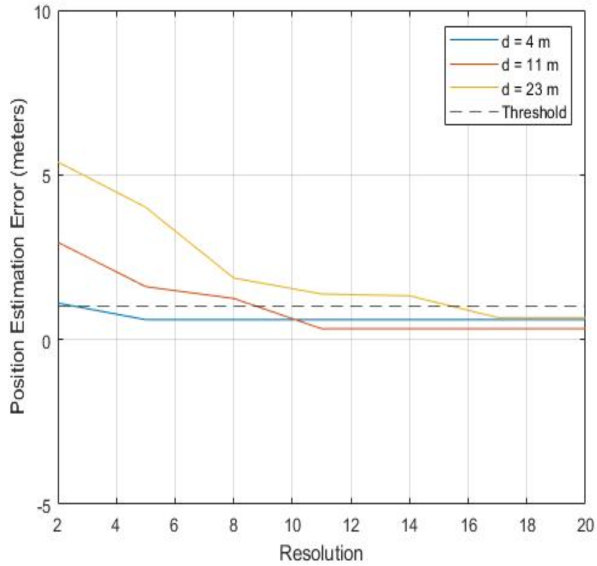

Figure 4.3: Effect of $d_{\text{IRS-UE}}$ on resolution convergence

codebook.

4.3 Effect Of Number Of Clusters and Number Of Rings

IRS assisted angular estimation method utilized varying size and high number of clusters. In order to observe the effect of number of clusters, we have taken a circular cell of radius, R = 100 meter with M = 200 users uniformly distributed within it.

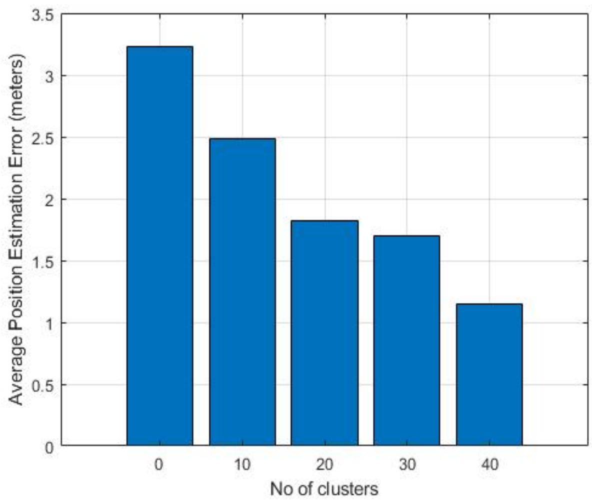

Figure 4.4: Number of clusters vs Average Position Estimation Error

We can see from figure 4.4, as number of clusters increase, average position estimation error drops. This is due to better SNR at the users, since, as the number of cluster increase, the distance between the users in a cluster and their distance from the dedicated IRS reduces.

Apart from number of clusters, the effect of varying cluster size was also analyzed. As we move towards far away users, the SNR drop is very high which might lead to poor angular estimation. In order to balance this issue, the size of clusters was reduced as we move further away from BS and its affect was observed on the performance. 100 users are equally divided among each ring and the overall radius of the cell is taken as R = 100 meter. Total number of clusters were fixed as 40. Each ring corresponds to certain distance range from the BS at the center. Which in effect means that, each ring corresponds to a certain cluster size. It can be seen from Figure

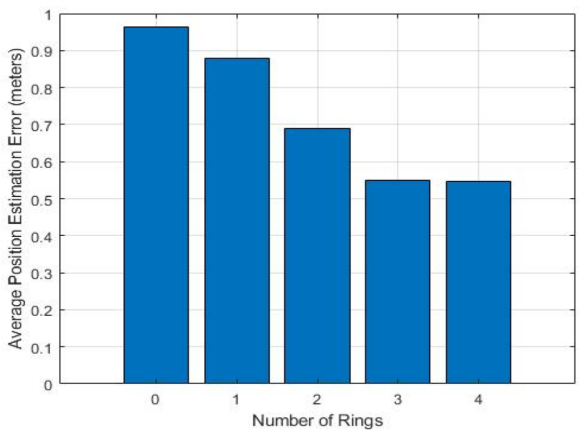

Figure 4.5: Number of rings vs Average Position Estimation Error for higher number of IRSs

4.5 that as the cluster size reduces for farther users, while keeping total number of clusters constant, position estimation error drops.

Furthermore, if there is a tighter constraint on the number of IRSs that can be deployed in the cell, then dividing cell in too many rings may lead to poor performance. We limit the number of IRSs(i.e., number of clusters) to 10 and take the same cellular structure,i.e., 100 meter radius and 100 users uniformly distributed within it. We can see from figure 4.6 that for lower number of IRSs, taking higher number of rings leads to poor performance.

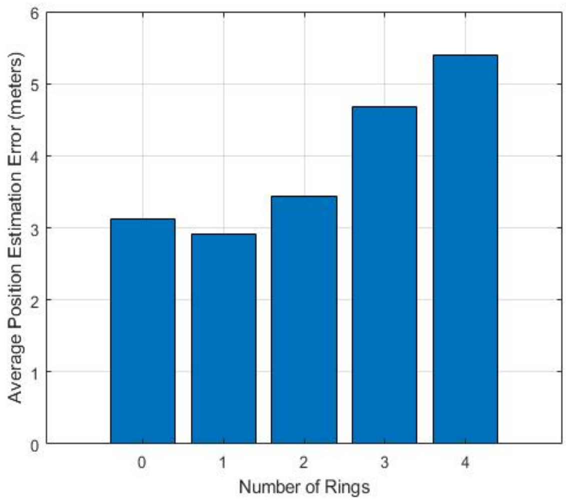

Figure 4.6: Number of rings vs Average Position Estimation Error for lower number of IRSs

Chapter 5

Conclusion and Future Work

5.1 Conclusion

We have successfully designed and implemented the IRS assisted system to determine positions of all the users using angular estimation. We showed how our proposed system provides superior performance compared to a simple base station based estimation of user's position. We also demonstrated, how dividing users into clusters and placing a dedicated IRS for each cluster further improves performance. We used CRLB to justify close placement and high element utilization on IRS. Furthermore, we showed the effect of different cluster sizes on performance. We also successfully implemented hierarchical codebooks and were able to establish its efficiency over exhaustive search.

5.2 Future Work

The main focus of our work was regarding angular estimation of user's position relative to the base station. It can be extended towards distance estimation by utilizing RSSI or using multiple anchor points to triangulate the user's position. Apart from this, further analysis can be done regarding optimization of number of clusters and number of rings in the cell.

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