

**ESTIMATING THE NUMBER OF ACTIVE DEVICES  
WITHIN A FIXED AREA USING WI-FI MONITORING**

A Thesis

by

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## ABSTRACT

In various situations, there is a need to estimate the number of active devices within a specific area. This thesis offers one possible approach to accomplish this task. It focuses on estimating the number of devices in a certain area based on monitoring and processing Wi-Fi metadata which includes the Received Signal Strength Indicator. To accomplish this goal, four sensing devices are placed at the corners of a rectangular area. These sensing devices observe and record local data traffic, along with the received signal strength associated with each packets. For each sensing device, two types of frontends are considered, namely directional and isotropic antennas. Each sensing device retrieves the received signal strength indicators and the media access control addresses from the 802.11 frames packets transmitted by nearby active wireless devices. The estimator takes the received signal strength indicators as input and infers the number of active Wi-Fi devices inside the area of interest. Two algorithms, bayesian and maximum-likelihood, are employed for estimation purposes. Overall performance is used to compare and contrast the systems implemented with directional antennas and isotropic antennas, respectively. Theoretical and experimental results both hint at performance improvements when using directional antennas, when compare to standard isotropic antennas.

This dissertation work is dedicated to my advisors - Dr. J.F.Chamberland, my father, my mother, my friends for their support through out the process.

## **ACKNOWLEDGMENTS**

This section is also optional, limited to four pages. It must follow the Dedication Page (or Abstract, if no Dedication). If listing preliminary pages in Table of Contents, include Acknowledgments. Heading (ACKNOWLEDGMENTS) is bold if major headings are bold. It should be in same type size and style as text. So does vertical spacing, paragraph style, and margins.

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## **NOMENCLATURE**

|       |   |
|-------|---|
| RSSI  | Received Signal Strength Indicator                                      |
| MAC   | Media Access Control  |
| OGAPS | Office and Graduate and Professional Studies at Texas<br>A&M University |
| B/CS  | Bryan and College Station   |
| TAMU  | Texas A&M University  |

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# 1 INTRODUCTION

Occupancy estimation refers to the problem to estimate the number of people inside a certain area. This topic has attracted lots of interests for years due to its importance. There are several potential applications that can benefit from occupancy estimation. In smart building automation systems, getting the knowledge of the level of occupancy, it is able to optimize the energy cost over the control of temperature and ventilation. This can result in a large amount of energy saving [1, 2]. In navigation systems, providing road occupancy traffic information will allow users find out best route to the destination. In [3], the author proposed a road monitoring system that encompass UMTS and GPRS data collection. Under an emergency circumstance, a proper occupancy estimation may help the government guide the evacuation of crowds.

Recent years, the number of Wi-Fi access points and the number of Wi-Fi client devices have been increasing dramatically. This growth in Wi-Fi infrastructure leads to large amounts of data being transmitted over wireless networks. Cisco Systems predicts in their Visual Network Index that 55 percent of total mobile data traffic will be offloaded onto fixed networks through Wi-Fi access points and femtocells by 2020 [4]. This means Wi-Fi is becoming a notable data source. Since Wi-Fi signals can tell us about our environment. A lot of attentions are drawn into this area, like self-localization, source localization and occupancy estimation [5, 6].

As well, we have witnessed the rapid development of mobile technology which is led

by large amount of smartphone users. Smartphone supports real-time communication and information access, and it is with an advanced mobile operating system which combines features of a personal computer operating system with other features useful for mobile or handheld use. This will bring influence on human activity. The global smartphone penetration rate has growing fast over these years. According to eMarketer's prediction in [7], smartphone user penetration as percentage of total global population will be 34.64% by 2019. Now in the U.S., 197.4 million people owned smartphones (79.3 percent mobile market penetration) during the three months ending in December 2015 according to com-Score's report [8]. This rapid development demands an improved manufacturing process. As the result, mass production involved in smartphone technology have decreased the cost of smartphone components. This fact makes smartphones prize-friendly to users. Notably smartphone operation systems also play important roles in mobile devices. For instance, Android system provide the manufacturer a tool to produce multi-platform application for smartphone. This makes development procedure heaper and gets devices in the hands of more people.

Overall, the continuously growth in mobile technology attracts more attentions into this field. In this work, we are interested in the occupancy estimation based on Wi-Fi activity of the users. A good understanding of the wireless channel is the key to analyze the communication systems. With this thought in mind, we will discuss important concepts in channel model like path loss, shadow fading and multipath propagation.

Path loss refers to the attenuation in the transmitted signal while propagating from

the transmitter (Tx) to the receiver (Rx). Typically received signal power is a function of distance between Tx and Rx. The simplest path loss model is used for unobstructed line-of-sight(LOS) signal path in free space propagation. Under this model, the received signal is given as

$$P_R = P_T G_T G_R \frac{\lambda^2}{4\pi d^2} \quad (1.1)$$

where  $P_T$  is the transmitted power,  $G_T$  and  $G_R$  are the transmit and receive antennas gains, respectively,  $\lambda$  is the transmitted carrier wavelength, and  $d$  is the distance between the Tx and the Rx. Thus, the received power falls off proportional to the ratio of wavelength over distance squared. We also find the relation between path loss and wave length. Shorter wave length, higher path loss. Though simple, the free space path loss model cannot be accurate in real environment. Therefore we need to take more factors into consideration.

In the previous path loss model, we assume the path loss to be a constant if the distance is given. However in reality, the presence of the obstacles like buildings and trees between transmitter and receiver may bring random variations in path loss. This effect due to changes in scattering, reflecting and diffracting surfaces in the propagation environment is called shadowing [9]. Considering the shadowing, the received signal power is given as

$$P_R = P_T G_T G_R S \quad (1.2)$$

where  $P_L$  and  $S$  correspond to the path loss and the shadow fading factor, respectively. Here  $S$  is a random variable. Experiment results show that a log-normal distribution function provides a good match to the empirical pdf of the shadow fading component [10]. Therefore the pdf of  $S$  can be approximated as the pdf of Gaussian random variable when  $S$  is

expressed in  $dB$  domain.

$$f_{S_s}(s) = \frac{1}{\sqrt{2\pi}\sigma_s} \exp\left(-\frac{s^2}{2\sigma_s^2}\right) \quad (1.3)$$

where  $\sigma_s$  is the standard deviation of shadowing. Typically  $\sigma_s$  is between 5-10  $dB$ .

Multipath fading occurs as a result of the transmitted signal reflection, diffraction, and/or scattering on objects before reaching the destination. Multiple copies of signal may arrive at different phases. Multipath fading may also cause inter symbol interface. Compared with shadowing fading, multipath fading is a short-term factor that generally causes smaller effect to the signal power. Therefore the multipath fading is also called small-scale fading. Some model such as Rayleigh fading and Rician fading can be used for multipath fading [9]. Rayleigh fading is a reasonable model when there are many objects in the environment that scatter the radio signal before it arrives at the receiver. However, when a LOS or a strong reflected path, termed specular component, also arrives at the receiver, the fading is more appropriately modeled by a Rician distribution [11]. Several different models such as Okumura, Hata, Walfish-Ikegami are proposed to model different environments like urban, rural and indoor area [11].

Current literature on occupancy estimation are mainly based on either images or RF signals. Approaches based on camera use captured images to estimate the number of people in a crowded scene [12, 13, 14]. Still, in such camera-based approaches, estimation accuracy can be affected by many factors such as brightness and image resolution. In addition, camera-based approaches typically lead to high deployment cost which makes it inconvenient to deploy in reality. On the other hand, occupancy estimation based on RF

signals is more promising. This category consists several methods. Passive infrared sensor is one of the common technologies use in the past few years. In [15], they proposed an occupancy estimation system which is able to adjust with movement of the people inside the building. The author shows that about 5% more energy can be saved by using smart occupancy sensor as compared to non-adapting fixed time-delay sensors. In [16], an indoor occupancy estimation using ultrasonic chirps is proposed. The author shows that the average error in percentage to the maximum capacity of the room is around 5%. However it is an active sensing system, if multiple transducers are placed in the same room, each transducer will interfere with others. Some other methods involved Bluetooth [17] and Wi-Fi [18]. However, the short transmission range limits the performance of Bluetooth-based methods. A research compared Wi-Fi and Bluetooth approaches [19]. In their work, the authors stipulate that Wi-Fi has advantage over Bluetooth in monitoring people, due to shorter discovery time and higher detection rates. According to their results, more than 90% of scanned unique MAC addresses in all places are Wi-Fi addresses; the popularity of using Wi-Fi devices is therefore significantly higher than that of Bluetooth devices, which means occupancy estimation using Wi-Fi is much more convenient in practice. In [20], the author proposes FCC, a device-Free Crowd Counting approach based on channel state information measurements. In [21], the author develops a new approach for estimating the total number of people walking in an area with only Wi-Fi power measurements between a pair of stationary transmitter/receiver antennas. In that case they do not need the measurement of channel state information.

In this thesis, we are interested in estimating the number of active devices in a fixed area using Wi-Fi metadatas. Modern mobile devices equipped with Wi-Fi modules transmit Wi-Fi messages periodically. Therefore, this provides a means to estimate occupancy by passively listening to Wi-Fi packets. More specifically, by deploying Wi-Fi monitoring devices in an area of interest, it is possible to detect these Wi-Fi transmissions. Each acquired Wi-Fi packet contains a unique MAC address. This information can be augmented by the received signal strength indicator (RSSI) of the captured signal. In the current context, the MAC address serves as a device identifier, whereas the RSSI provides partial information about the physical distance between the transmitter and the receiver. This information is helpful in inferring the device location status. The existence of pcap, an application programming interface for capturing network traffic, and wireshark, a network protocol analyzer, makes the Wi-Fi traffic analysis more straightforward.

In the research, we focus on occupancy estimation based on Wi-Fi packets and we analyze the benefits associated with using directional antennas. On the one hand, we are going to introduce two stochastic estimation schemes. One is Bayes estimation scheme and the other is maximum likelihood scheme. On the other hand, we will investigate the benefit by using directional antennas in monitoring devices. Because the radiation pattern of antenna will influence the RF propagation. It is naturally to think of the potential impacts it brings to use directional antennas. We employ numerical simulations to compare the performance of different schemes corresponding to sensing devices with directional antennas and isotropic antennas. In the simulation, we assume that four sensing devices

are located in the four corners of rectangular target area. The training RSSI values are assumed to obey free-space path loss model as well. Our results indicate if directional antennas are used, the error rate decreases considerably. In addition, our findings are further supported through outdoor experimentation. The testbed is implemented in a line-of-sight environment, with four sensing devices deployed at the corners of the area of interest.

The remainder of this thesis is organized as follows. In Section 2, we explain our problem formulation and develop our probability model. In Section 3, we propose two algorithms for occupancy estimation. These schemes are evaluated through numerical simulations in Section 4. We then discuss experimental result, along with description of experiment setup in Section 5. Finally, we offer concluding remarks in Section 6.



## 2 SYSTEM MODEL AND PROBLEM FORMULATION

Wi-Fi based occupancy estimation is attractive because it only require simple sensing device. Meanwhile it can benefit from local Wi-Fi network and the high penetration rate of smartphone. The existence of tools like pcap and wireshark makes monitoring Wi-Fi environment a straight forward work. In this thesis, we will extract the RSSI and MAC address for the purpose of occupancy estimation. As is discussed above, the RSSI is related to the distance between Rx and Tx. Therefore we can infer the location information by RSSI. However RSSI does not only depend on distance, some other factors like noise and fading will also influence it. As such, a proper wireless channel model is needed to take care of this situation.

### 2.1 Wireless Channel Model

A common wireless environment can be express by

$$r(t) = g(d)s(t) + w(t)$$

where  $r(t)$  represents received signal.  $g(d)$  the function of distance is the power gain which is related to several factors including the mean path loss, shadow fading and antenna gain.  $s(t)$  denotes the sent signal and  $w(t)$  is additive white Gaussian noise. Here we use the log-normal channel model. So the received power for a given distance between transmitter and receiver can be expressed as

$$P_d[\text{dBm}] = A + B\log_{10}(d) + L_s + G_a \quad (2.1)$$

where  $A$  is a combination of the transmitted signal power and average path loss and  $B$  represents the path loss coefficient.  $L_s$  is an independent and identically distributed Gaussian random variable which represents shadowing.  $G_a$  is the antenna gain. Note that the mean of  $L_s$  can be added in  $A$ , thus we assume  $L_s$  is a zero mean random variable,  $L_s \sim \mathcal{N}(0, \sigma_s^2)$ .  $\sigma_s$  is the variance of shadowing component. Therefore in the logarithmic domain, the density function of  $L_s$  can be written as

$$f_{L_s}(\ell) = \frac{1}{\sqrt{2\pi}\sigma_s} \exp\left(-\frac{\ell^2}{2\sigma_s^2}\right)$$

Here the variance can be estimated by sample data set. An unbiased estimator for the variance is given by [22]

$$\sigma_s^2 = \frac{1}{N-1} \sum_1^N (l_k - \mu_s)^2$$

where  $N$  is the sample size,  $l_k$  forms the data set, and points are expressed in the logarithmic domain.

Now the goal is to estimate the wireless channel parameter  $A$  and  $B$ . Here we are going to use the least square method, which minimizes the sum of the squares of the offsets. For a linear least square problem given by,

$$f(x, \beta) = \sum_{j=1}^m \beta_j \phi_j(x)$$

where the function  $\phi_j$  is a function of  $x$ ,  $\beta$  is the parameter vector to be estimated. Letting

$$X_{ij} = \frac{\partial f(x_i, \beta)}{\partial \beta_j} = \phi_j(x_i)$$

$\beta$  is given by

$$\hat{\beta} = (X^T X)^{-1} X^T y$$

For the least square problem defined in 2.1, letting

$$y = \begin{bmatrix} p_1 \\ \vdots \\ p_N \end{bmatrix}$$

$$X = \begin{bmatrix} 1 & \log_{10}(d_1) \\ \vdots & \vdots \\ 1 & \log_{10}(d_N) \end{bmatrix}$$

where  $y$  denotes the received power at distance  $d$ . Then the estimator of  $A$  and  $B$  is given as

$$\begin{bmatrix} A \\ B \end{bmatrix} = (X^T X)^{-1} X^T y$$

The variance of  $L_s$ , the shadow fading component, is computed by normalizing the residual error

$$\sigma_s^2 = \frac{1}{N-1} y^T (I - X(X^T X)^{-1} X^T) y$$

## 2.2 Problem Formulation

Consider a scenario where several wireless devices are randomly positioned nearby an area of interest. To simplify the problem, we assume the area to be rectangular shape. Four RF monitoring devices are located at the corners of this region. Each monitoring device has information concerning its own location and orientation. The radiation pattern of antenna attached to each monitoring device is known as well. In our system model, all of the monitoring devices are connected to the Internet and send the captured data to a process

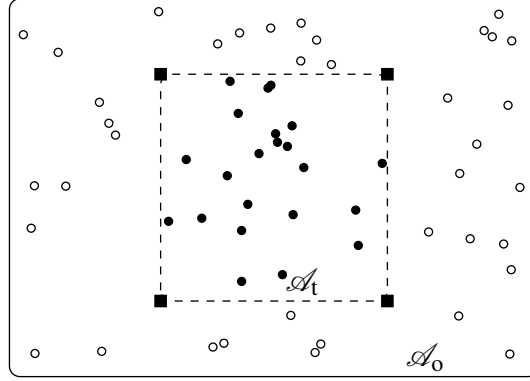


Figure 2.1: The periphery of target area delineated by dashed line. Squares at the corners of target area denote the locations of monitoring devices, equipped with directional antennas. Clients within the zone of interest are in black, whereas outside agents appear as white. The objective is to estimate occupancy within target area.

center for inference. Several wireless clients carried by users are randomly located near this area, they can be inside or outside the area of interest. The wireless clients transmit data packets periodically and consequently they can be easily detected by the monitoring devices. Since each wireless client has a unique MAC address, the packets transmitted from different clients can be distinguished. Throughout, we use  $\mathcal{A}_t$  to represent the target area and  $\mathcal{A}_o$  to represent its complement. A notional diagram of the framework is shown in Fig. 2.1 In this thesis, we assume the wireless clients are quasi-static and each client is equipped with an isotropic antenna. Thus the orientation of the wireless clients does not matter. For convenience, we use a single vector to denote the locations of the wireless clients.

$$\underline{\mathbf{U}} = (\mathbf{U}_1, \dots, \mathbf{U}_{n_a}). \quad (2.2)$$

where  $n_a$  is the number of the detected clients. We also assume that the signal captured by a monitoring device comes from a line-of-sight path. Therefore, signal strength subscribes

to a free-space transmission model. The received signal strength from client  $j$  to sensing device  $i$  can be expressed in log-normal channel model.

$$P_{ij}[\text{dBm}] = A + B \log_{10}(d_{ij}) + L_{ij} + G_i(\phi_{ij}) \quad (2.3)$$

where  $A$  and  $B$  are the mean decay parameters,  $d_{ij}$  is the Euclidean distance between the client  $j$  and sensing device  $i$ . the distance is equal to

$$d_{ij} = d(\mathbf{s}_i, \mathbf{u}_j) = \sqrt{(u_{1j} - s_{1i})^2 + (u_{2j} - s_{2i})^2}$$

$L_{ij}$  represent shadow fading and  $G_i(\cdot)$  is the antenna gain function of the sensing device. Parameter  $\phi_{ij}$  denotes the angle of the signal transmission direction, which can be expressed as

$$\phi_{ij} = \angle(\mathbf{s}_i, \mathbf{u}_j) = \text{atan2}(u_{2j} - s_{2i}, u_{1j} - s_{1i})$$

The shadow fading components  $\{L_{ij}\}$  are assumed to be independent and identically log-normal distributed random variables. In the logarithmic domain, the probability density function is

$$f_{L_{ij}}(\ell) = \frac{1}{\sqrt{2\pi}\sigma_s} \exp\left(-\frac{\ell^2}{2\sigma_s^2}\right) \quad (2.4)$$

where  $\sigma_s$  is the standard deviation of shadowing. The observed information from the four sensing devices form a power matrix  $\mathbf{P} = (\mathbf{P}_1, \dots, \mathbf{P}_{n_a})$ . The vector element  $\mathbf{P}_j = (P_{1j}, P_{2j}, P_{3j}, P_{4j})$  contains signal strength of wireless client  $j$  detected by four sensing devices. We assume the number and locations of wireless clients located inside the area of interest form a Poisson point process with intensity  $\lambda_t$ . Therefore, the probability of  $r_t$

wireless clients inside the target area is

$$\Pr(R_t = r_t) = \frac{(\lambda_t A_t)^{r_t}}{r_t!} e^{-A_t \lambda_t} \quad r_t = 0, 1, \dots$$

where  $R_t$  is the number of clients inside.  $A_t$  is the area of the target region. Similarly, we get the probability of  $r_o$  wireless clients outside the target area.

$$\Pr(R_o = r_o) = \frac{(\lambda_o A_o)^{r_o}}{r_o!} e^{-A_o \lambda_o} \quad r_o = 0, 1, \dots$$

where  $R_o$  is the number of clients outside.  $A_o$  is the area of the complimentary of target region.  $\lambda_o$  is a Poisson intensity parameter. The inference task is to estimate occupancy based on the power matrix data set  $\mathbf{P}$  which is collected by the sensing devices.

### 3 ESTIMATION SCHEMES

In this section, we introduce two estimation schemes employed in this thesis. Bayes estimation and maximum likelihood estimation are considered to be applied under different scenarios. If the estimation process is applied repetitively over time, then acquired data can be employed to gain accurate estimates for  $\lambda_t$  and  $\lambda_o$ . In other words,  $\lambda_t$  and  $\lambda_o$  are considered known. In this case the Bayes estimation is employed. On the other hand, if the occupancy estimation is applied to an area of interest once, then we should use classic scheme, such as maximum likelihood estimation which assumes a uniform prior distribution of the parameters

#### 3.1 Bayes Estimation

In Bayes estimation scheme, we assume the Poisson intensity parameters  $\lambda_t$  and  $\lambda_o$  are known. Our objective is to estimate the number of clients inside the target area based on observed data  $\underline{\mathbf{P}}$ . First we need to get the posterior distribution of  $R_t$ , given  $\underline{\mathbf{P}}$

$$\begin{aligned} \Pr(R_t = r_t | \underline{\mathbf{P}} = \underline{\mathbf{p}}) &= \int_{\{\underline{\mathbf{u}}: R_t(\underline{\mathbf{u}})=r_t, R_o(\underline{\mathbf{u}})=r_o\}} f_{\underline{\mathbf{U}}|\underline{\mathbf{P}}}(\underline{\mathbf{u}}|\underline{\mathbf{p}}) d\underline{\mathbf{u}} \\ &= \int_{\{\underline{\mathbf{u}}: R_t(\underline{\mathbf{u}})=r_t, R_o(\underline{\mathbf{u}})=r_o\}} \frac{f_{\underline{\mathbf{P}}|\underline{\mathbf{U}}}(\underline{\mathbf{p}}|\underline{\mathbf{u}}) f_{\underline{\mathbf{U}}}(\underline{\mathbf{u}})}{f_{\underline{\mathbf{P}}}(\underline{\mathbf{p}})} d\underline{\mathbf{u}} \end{aligned} \quad (3.1)$$

where  $\underline{\mathbf{U}}$  is the location vector containing the random positions of the wireless clients. The location vector includes lots of information. For example, the size of  $\underline{\mathbf{U}}$  is the number of active wireless clients. According to location vector, we can get the number of wireless clients inside or outside the target area. Thus  $R_t$  and  $R_o$  are functions of  $\underline{\mathbf{U}}$ . Because the

outside and inside Poisson processes are independent, the distribution of  $\underline{\mathbf{U}}$  can be written as

$$\begin{aligned}
f_{\underline{\mathbf{U}}}(\underline{\mathbf{u}}) &= \frac{1}{A_t^{R_t(\underline{\mathbf{u}})}} \frac{(\lambda_t A_t)^{R_t(\underline{\mathbf{u}})}}{(R_t(\underline{\mathbf{u}}))!} e^{-A_t \lambda_t} \\
&\frac{1}{A_o^{R_o(\underline{\mathbf{u}})}} \frac{(\lambda_o A_o)^{R_o(\underline{\mathbf{u}})}}{(R_o(\underline{\mathbf{u}}))!} e^{-A_o \lambda_o} \\
&= \frac{\lambda_t^{R_t(\underline{\mathbf{u}})}}{(R_t(\underline{\mathbf{u}}))!} \frac{\lambda_o^{R_o(\underline{\mathbf{u}})}}{(R_o(\underline{\mathbf{u}}))!} e^{-A_t \lambda_t - A_o \lambda_o}
\end{aligned} \tag{3.2}$$

For a wireless client  $j$ , the distribution of the received power vector  $\mathbf{P}_j$  given a specific location  $\mathbf{u}_j$  is equal to

$$\begin{aligned}
f_{\mathbf{P}_j|\mathbf{U}_j}(\mathbf{p}_j|\mathbf{u}_j) &= \prod_{i=1}^{n_s} f_{L_{ij}}(p_{ij} - A - B \log_{10}(d_{ij}) - G_i(\phi_{ij})) \\
&= \frac{1}{(2\pi\sigma_s^2)^{\frac{n_s}{2}}} \prod_{i=1}^{n_s} e^{-\frac{(p_{ij} - A - B \log_{10}(d_{ij}) - G_i(\phi_{ij}))^2}{2\sigma_s^2}} \\
&= (2\pi\sigma_s^2)^{-\frac{n_s}{2}} e^{-\frac{\sum_{i=1}^{n_s} (p_{ij} - A - B \log_{10}(d_{ij}) - G_i(\phi_{ij}))^2}{2\sigma_s^2}}
\end{aligned} \tag{3.3}$$

The conditional distribution of  $\underline{\mathbf{P}}$  given  $\underline{\mathbf{U}} = \underline{\mathbf{u}}$ , is

$$f_{\underline{\mathbf{P}}|\underline{\mathbf{U}}}(\underline{\mathbf{p}}|\underline{\mathbf{u}}) = \prod_{j=1}^{n_a} f_{\mathbf{P}_j|\mathbf{U}_j}(\mathbf{p}_j|\mathbf{u}_j) \tag{3.4}$$



With the conditional distribution of  $\underline{\mathbf{P}}$  given  $\underline{\mathbf{U}} = \underline{\mathbf{u}}$  and distribution of  $\underline{\mathbf{U}}$ , we can compute the marginal distribution of  $\underline{\mathbf{P}}$ ,

$$\begin{aligned}
& \Pr(R_t = r_t | \underline{\mathbf{P}} = \underline{\mathbf{p}}) \\
&= \int_{\{\underline{\mathbf{u}}: R_t(\underline{\mathbf{u}}) = r_t, R_o(\underline{\mathbf{u}}) = r_o\}} \frac{f_{\underline{\mathbf{P}}|\underline{\mathbf{U}}}(\underline{\mathbf{p}}|\underline{\mathbf{u}}) f_{\underline{\mathbf{U}}}(\underline{\mathbf{u}})}{f_{\underline{\mathbf{P}}}(\underline{\mathbf{p}})} d\underline{\mathbf{u}} \\
&= \int_{\{\underline{\mathbf{u}}: R_t(\underline{\mathbf{u}}) = r_t, R_o(\underline{\mathbf{u}}) = r_o\}} \prod_{j=1}^{n_a} \frac{f_{\underline{\mathbf{P}}_j|\underline{\mathbf{U}}_j}(\underline{\mathbf{p}}_j|\underline{\mathbf{u}}_j)}{f_{\underline{\mathbf{P}}}(\underline{\mathbf{p}})} \\
&\quad \times \frac{\lambda_t^{R_t(\underline{\mathbf{u}})}}{(R_t(\underline{\mathbf{u}}))!} \frac{\lambda_o^{R_o(\underline{\mathbf{u}})}}{(R_o(\underline{\mathbf{u}}))!} e^{-A_t \lambda_t - A_o \lambda_o} d\underline{\mathbf{u}} \\
&= \sum_{\{\mathbb{I} \subset [n_a]: |\mathbb{I}| = r_t\}} \frac{\lambda_t^{r_t} \lambda_o^{r_o} e^{-A_t \lambda_t - A_o \lambda_o}}{r_t! r_o! f_{\underline{\mathbf{P}}}(\underline{\mathbf{p}})} \\
&\quad \times \prod_{j \in \mathbb{I}} \mathcal{J}_{\mathcal{A}_t}(j) \prod_{j \in \mathbb{I}^c} \mathcal{J}_{\mathcal{A}_o}(j)
\end{aligned}$$

Computing this conditional distribution of  $R_t$  given  $\underline{\mathbf{P}}$  may appear difficult as it needs to take sums over subsets of  $\{1, \dots, n_a\}$ . However, by using generating functions, the posterior distribution can be calculated more efficiently [23].

Thus, the mean of the posterior distribution of  $R_t$  condition upon  $\underline{\mathbf{P}}$  is the Bayes estimator.

$$\begin{aligned}
\hat{R}_t(\underline{\mathbf{p}}) &= \mathbb{E}[R_t | \underline{\mathbf{P}} = \underline{\mathbf{p}}] \\
&= \sum_{r_t=0}^{n_a} r_t \Pr(R_t = r_t | \underline{\mathbf{P}} = \underline{\mathbf{p}})
\end{aligned} \tag{3.5}$$

We adopt Bayesian mean squared error to evaluate the performance of the estimator, which is given below.

$$\text{BMSE}[\hat{R}_t] = \mathbb{E}[(\hat{R}_t(\underline{\mathbf{P}}) - R_t)^2]. \tag{3.6}$$

This BMSE can be approximated by taking the average over samples numerically.

$$\text{BMSE} [\hat{R}_t] \approx \frac{1}{M} \sum_{m=1}^M \left( \hat{R}_t^{(m)} \left( \underline{\mathbf{p}}^{(m)} \right) - R_t^{(m)} \right)^2 \quad (3.7)$$

### 3.2 Maximum likelihood estimation

In this section, we assume the Poisson intensity parameters  $\lambda_t$  and  $\lambda_o$  are unavailable. In this case we will deploy classical approach and adopt maximum-likelihood estimation [24]. The distribution of  $\underline{\mathbf{U}}$  can be written as

$$f_{\underline{\mathbf{U}}}(\underline{\mathbf{u}}; \lambda_t, \lambda_o) = \frac{\lambda_t^{R_t(\underline{\mathbf{u}})}}{(R_t(\underline{\mathbf{u}}))!} \frac{\lambda_o^{R_o(\underline{\mathbf{u}})}}{(R_o(\underline{\mathbf{u}}))!} e^{-A_t \lambda_t - A_o \lambda_o} \quad (3.8)$$

The likelihood function is a function with two parameters,  $\lambda_t$  and  $\lambda_o$

$$\begin{aligned} \mathcal{L}(\lambda_t, \lambda_o; \underline{\mathbf{p}}, \underline{\mathbf{u}}) &= f_{\underline{\mathbf{p}}|\underline{\mathbf{U}}}(\underline{\mathbf{p}}, \underline{\mathbf{u}}; \lambda_t, \lambda_o) \\ &= f_{\underline{\mathbf{p}}|\underline{\mathbf{U}}}(\underline{\mathbf{p}}|\underline{\mathbf{u}}) f_{\underline{\mathbf{U}}}(\underline{\mathbf{u}}; \lambda_t, \lambda_o) \end{aligned} \quad (3.9)$$

By computing the integral over  $\underline{\mathbf{U}}$ , we can get the marginal likelihood function

$$\begin{aligned} \mathcal{L}(\lambda_t, \lambda_o; \underline{\mathbf{p}}) &= \int_{\{\underline{\mathbf{u}}: R_t(\underline{\mathbf{u}}) + R_o(\underline{\mathbf{u}}) = n_a\}} f_{\underline{\mathbf{p}}|\underline{\mathbf{U}}}(\underline{\mathbf{p}}|\underline{\mathbf{u}}) f_{\underline{\mathbf{U}}}(\underline{\mathbf{u}}; \lambda_t, \lambda_o) d\underline{\mathbf{u}} \\ &= e^{-A_t \lambda_t - A_o \lambda_o} \sum_{(r_t, r_o): r_t + r_o = n_a} \frac{\lambda_t^{r_t} \lambda_o^{r_o}}{r_t! r_o!} \sum_{\{\mathbb{I} \subset [n_a]: |\mathbb{I}| = r_t\}} \prod_{j \in \mathbb{I}} \mathcal{J}_{\mathcal{A}_t}(j) \prod_{j \in \mathbb{I}^c} \mathcal{J}_{\mathcal{A}_o}(j) \end{aligned} \quad (3.10)$$

This is a two-dimensional optimization, but we can simplify it to a one-dimensional optimization problem by following property.

$$\max_{\lambda_t, \lambda_o} \mathcal{L}(\lambda_t, \lambda_o; \underline{\mathbf{p}}) = \max_{\alpha} \mathcal{L}\left(\frac{n_a}{A_t} \alpha, \frac{n_a}{A_o} (1 - \alpha); \underline{\mathbf{p}}\right) \quad (3.11)$$

where  $\alpha$  within the interval  $[0, 1]$ . Therefore, we rewrite the likelihood function in terms of  $\alpha$

$$\begin{aligned}
& \mathcal{L} \left( \frac{n_a}{A_t} \alpha, \frac{n_a}{A_o} (1 - \alpha); \underline{\mathbf{p}} \right) \\
&= \sum_{(r_t, r_o): r_t + r_o = n_a} \frac{e^{-n_a} n_a^{n_a}}{r_t! r_o!} \left( \frac{\alpha}{A_t} \right)^{r_t} \left( \frac{1 - \alpha}{A_o} \right)^{r_o} \\
&\quad \times \sum_{\{\mathbb{I} \subset [n_a]: |\mathbb{I}| = r_t\}} \prod_{j \in \mathbb{I}} \mathcal{J}_{\mathcal{A}_t}(j) \prod_{j \in \mathbb{I}^c} \mathcal{J}_{\mathcal{A}_o}(j)
\end{aligned} \tag{3.12}$$

Now, we can use numerical methods to get the values of  $\lambda_t$  and  $\lambda_o$  which maximize the likelihood function. Once  $\lambda_t$  and  $\lambda_o$  are obtained, the maximum likelihood estimator can be calculated as

$$\begin{aligned}
\hat{R}_t(\underline{\mathbf{p}}) &= E_{\hat{\lambda}_t, \hat{\lambda}_o} [R_t | \underline{\mathbf{P}} = \underline{\mathbf{p}}] \\
&= \sum_{r_t=0}^{n_a} r_t \Pr(R_t = r_t | \underline{\mathbf{P}} = \underline{\mathbf{p}}; \hat{\lambda}_t, \hat{\lambda}_o)
\end{aligned} \tag{3.13}$$

We adopt mean squared error to evaluate the performance of estimator

$$\text{MSE} [\hat{R}_t] = E \left[ (\hat{R}_t(\underline{\mathbf{P}}) - R_t)^2 \right] \tag{3.14}$$

MSE can be approximated by taking the average over samples numerically.

$$\text{MSE} [\hat{R}_t] \approx \frac{1}{M} \sum_{m=1}^M \left( \hat{R}_t^{(m)}(\underline{\mathbf{P}}^{(m)}) - R_t^{(m)} \right)^2 \tag{3.15}$$

## 4 NUMERICAL SIMULATION SETUP AND RESULTS

In this section, we will introduce our simulation setup including the directional antenna model, the parameters of the channel and how we generate RSSI samples. The simulation results will be shown after that. The simulation code is written in python. In the simulation framework, the set up consists of four monitoring devices placed at the corners of the area of interest. All antennas attached to monitoring devices are pointing to the center of the area of interest. The target area is considered to be a square of dimension  $6\text{ m} \times 6\text{ m}$  inscribed in a larger square of dimension  $10\text{ m} \times 10\text{ m}$ . The two square areas share a same center point. We use  $A_t$  to denote the target area, while  $A_o$  denotes its complement. We will call target area inside region and call its complement outside region in the following text.

### 4.1 Antenna Characteristic

In our simulation, to analyze the effect of radiation characteristics of the sensing antennas on the estimation, isotropic antennas and directional antennas are considered. The antenna gain of isotropic antennas are zero in all directions. For the directional antennas, we adopt 3GPP antenna model in [25]. The directional antenna gains obey the following formula.

$$G_i(\phi_{ij}) = -\min \left\{ 12 \left( \frac{\phi_{ij} - \theta_i}{\theta_{3\text{dB}}} \right)^2, G_{\text{floor}} \right\} - G_{\text{avg}}$$

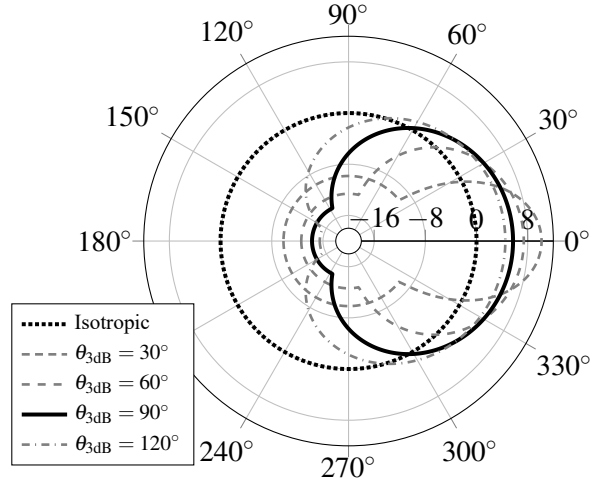


Figure 4.1: This graph depicts normalized antenna radiation patterns. The pointing direction is set to  $0^\circ$  and  $G_{\text{floor}} = 20$  dB.

where  $\theta_i$  is pointing direction of the antenna which is attached to monitoring devices  $i$ .

$\theta_{3\text{dB}}$  is the 3 dB beam-width of the radiation pattern.  $G_{\text{floor}}$  is a nominal attenuation floor.

$G_{\text{average}}$  is a normalization factor which equal to the average gain over  $\in (-180^\circ, 180^\circ]$ .

$$10 \log_{10} \left( \int_{-180}^{180} \frac{10^{-\frac{1}{10} \min \left\{ 12 \left( \frac{\phi_{ij} - \theta_i}{\theta_{3\text{dB}}} \right)^2, G_{\text{floor}} \right\}}}{360} d\phi_{ij} \right).$$

The antenna radiation pattern for various 3 dB beam-widths is shown in Fig.4.1.

## 4.2 Channel Characteristic

As mentioned in chapter 2, the channel model we applied is log-normal path loss model. The received signal power can be expressed as

$$P[\text{dBm}] = A + B \log_{10}(d) + L + G(\phi) \quad (4.1)$$

In this equation, the physical parameters are based on regulation issued by the Federal Communications Commission (FCC) and profiles of typical wireless environments. Ac-

cording to Friis transmission equation given below [26],

$$A = P_t + 20 \log_{10} \left( \frac{3 \times 10^8}{f_{\text{carrier}}} \right) - 20 \log_{10}(4\pi)$$

where  $P_t$  is the mobile devices transmission power. Here we set it to be 20 dBm.  $f_{\text{carrier}}$  is the frequency of Wi-Fi signal wave which is 2.462 GHz [27]. So  $A = -20.27 \text{ dBm}$ . We adopt path-loss parameter  $B$  to be -20 dBm which is the coefficient of free-space path loss. The logarithmic  $\sigma_s$  which represents variation in shadow fading, is set to 2.0 dBm.

### 4.3 Generating Data Set

As mentioned above, the inference task is based on received power matrix which is collected by monitoring devices. In the simulation, we need to create the sample data ourselves according to the antenna gain model and channel model discussed above. The parameter values we use to generate data set are summarized in Table 4.1. We generate data

Table 4.1: System parameters used during simulations.

| Physical Parameters            | Values                             |
|--------------------------------|------------------------------------|
| Nominal Power                  | $A = -20.27 \text{ dBm}$           |
| Free-Space Loss parameter      | $B = -20 \text{ dBm}$              |
| Logarithmic Standard Deviation | $\sigma_s = 2.0 \text{ dBm}$       |
| 3 dB Beam-width (directional)  | $\theta_{3\text{dB}} = 90^\circ$   |
| Antenna Floor                  | $G_{\text{floor}} = 20 \text{ dB}$ |

set as follow. We denote the location of the four monitoring devices as  $\{\mathbf{s}_i\} \ i \in 1, 2, 3, 4$ . First, we set a certain value  $\lambda$  which represents the aggregate Poisson rate across the two monitored regions (inside region and outside region) equal to 32. The splitting parameter

between two regions is  $\alpha$ . Thus

$$\lambda_t = \alpha \frac{\lambda}{A_t} \quad \lambda_o = (1 - \alpha) \frac{\lambda}{A_o}.$$

where  $\lambda_t$  is the Poisson rate of inside region and  $\lambda_o$  is the Poisson rate of outside region.

Once  $\lambda_t$  and  $\lambda_o$  are set,  $r_t$  the number of devices inside and  $r_o$  the number of devices outside are established using Poisson trials,

$$R_t \sim \frac{(A_t \lambda_t)^k}{k!} e^{-A_t \lambda_t} \quad R_o \sim \frac{(A_o \lambda_o)^k}{k!} e^{-A_o \lambda_o}.$$

Each of  $R_t = r_t$  devices inside the target area is independently assigned a location according to a uniform distribution. Likewise, each of  $R_o = r_o$  devices outside is independently assigned a location according to another uniform distribution. Therefore, we obtain the location vector  $\underline{\mathbf{U}} = \underline{\mathbf{u}}$  of the wireless clients. For each of the wireless clients, a collection of four received signal strength corresponding to four monitoring devices is computed according to 4.1. The shadow fading component  $L$  is generated following a log-normal distribution whose standard deviation  $\sigma_s = 2.0dBm$ . Finally, we get the sequence of power vectors  $\underline{\mathbf{p}} = (\mathbf{p}_1, \dots, \mathbf{p}_{n_a})$ , where vector  $\mathbf{p}_j$  corresponding to wireless client  $j$  contains four power strength received by four monitoring devices respectively. The proposed estimators will act on vector  $\mathbf{p}$

## 4.4 Performance Analysis

### 4.4.1 Bayes Estimation

We first consider the performance of Bayes estimation framework introduced in 3.1. As is discussed in the previous section, the Poisson rate of the two regions  $\lambda$ , the Poisson

rate of inside region  $\lambda_t$  and the Poisson rate of outside region  $\lambda_o$  have the following relation along with the splitting parameter  $\alpha$ .

$$\lambda_t = \alpha \frac{\lambda}{A_t} \qquad \lambda_o = (1 - \alpha) \frac{\lambda}{A_o}.$$

Where  $A_t$  the area of inside region is equal to 36,  $A_o$  the area of outside region is equal to 64.

We can plot performance results as a function of the splitting coefficient  $\alpha$ . The vertical axis represents the BMSE of Bayes estimator. The black curve in Fig. 4.2 shows the BMSE when the Bayes estimator operates on data collected using isotropic antennas. The red curve in Fig. 4.2 corresponds to four directional antennas located at the four corners of the target area and pointing directly at the center. These antennas have a 3 dB beam-width of  $\theta_{3\text{dB}} = 90^\circ$  and a nominal attenuation floor of  $G_{\text{floor}} = 20$  dB. Every point is obtained by averaging over fifty thousand trials.



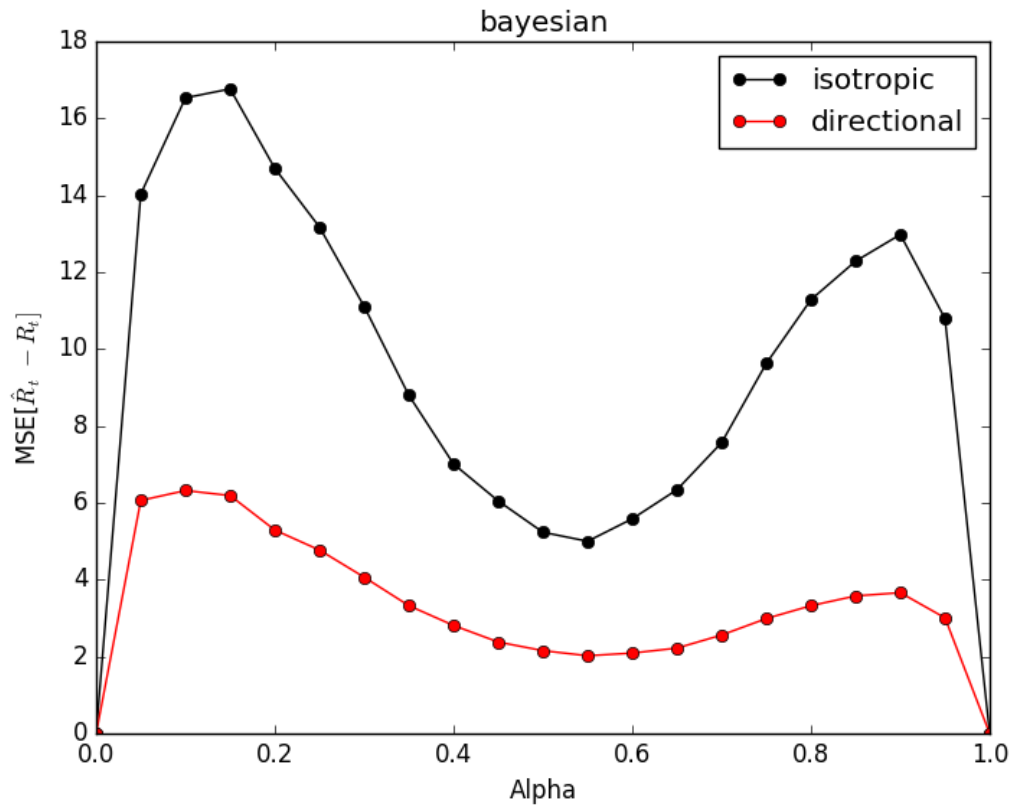


Figure 4.2: This graph shows Bayesian mean squared error as functions of splitting parameter. Black line correspond to performance of system equipped with isotropic antennas, whereas red line correspond to the performance of systems with directional antennas.

## **5 EXPERIMENT IMPLEMENTATION**

## **6 CONCLUSION**

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