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

A Thesis

by

HAI LI

Submitted to the Office of Graduate and Professional Studies of
Texas A&M University
in partial fulfillment of the requirement for the degree of

MASTER OF SCIENCE

Chair of Committee,	Jean-Francois Chamberland
Committee Members,	Gregory H. Huff
	Anxiao Jiang
	Tie Liu
Head of Department,	Miroslav M. Begovic

December 2016

Major Subject: Electrical and Computer Engineering

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.

I would like to thank Texas A&M University Office of Graduate and Professional Study to give me this chance to organize the Thesis LaTeX template. Special Thanks to JaeCee Crawford, Amy Motquin and Christine Brown for carefully reviewing this material.

NOMENCLATURE

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

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

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 comScore'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

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

where P_T is the transmitted power, G_T and G_R are the transmit and receive antennas gains, respectively, λ 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

$$P_R = P_T G_T G_R S \tag{1.2}$$

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.

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

where σ_s is the standard deviation of shadowing. Typically σ_s is between 5-10 dB.

Multipath fading occurs when multiple transmission waves are combined at the receiver, as a result of the transmitted signal reflection, diffraction, and/or scattering on objects before reaching the destination. 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 Ricean 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 our study, 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

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

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, $L_s \sim \mathcal{N}(0, \sigma_s^2)$. σ_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]

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

Consider a scenario where several wireless devices are randomly positioned nearby a rectangular area of interest. Four 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. All of the monitoring devices are connected to the Internet and send the captured data to a process center for inference. 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 $\mathscr{A}_t$ to represent the target area and $\mathscr{A}_o$ to represent its complement. In this study, we assume the wireless clients are quasi-static and each client is equipped with an isotropic antenna. For convenience, we use a single vector to denote the locations of the wireless clients.

$$\underline{\mathbf{U}} = (\mathbf{U}_1, \ldots, \mathbf{U}_{n_\mathrm{a}}). \tag{2.1}$$

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 as

$$P_{ij}[\mathrm{dBm}] = A + B\log_{10}(d_{ij}) + L_{ij} + G_i(\phi_{ij}) \tag{2.2}$$

where A and B are the mean decay parameters, d_{ij} is the Euclidean distance between the client j and sensing device i. L_{ij} represent shadow fading and $G_i(\cdot)$ is the antenna gain function of the sensing device. Parameter ϕ_{ij} denotes the angle of the signal transmission direction. 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

$$f_{L_{ij}}(\ell) = \frac{1}{\sqrt{2\pi}\sigma_\mathrm{s}} \exp\left(-\frac{\ell^2}{2\sigma_\mathrm{s}^2}\right) \tag{2.3}$$

where σ_s is the standard deviation of shadowing. The observed information from the four sensing devices form a power matrix $\underline{\mathbf{P}} = (\mathbf{P}_1, \ldots, \mathbf{P}_{n_\mathrm{a}})$. 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 λ_t. Therefore,

$$\Pr(R_\mathrm{t} = r_\mathrm{t}) = \frac{(\lambda_\mathrm{t} A_\mathrm{t})^{r_\mathrm{t}}}{r_\mathrm{t}!} e^{-A_\mathrm{t}\lambda_\mathrm{t}} \quad r_\mathrm{t} = 0, 1, \ldots$$

where R_{t} is the number of clients inside. A_{t} is the area of the target region. Similarly, we get

$$\Pr(R_{\mathrm{o}} = r_{\mathrm{o}}) = \frac{(\lambda_{\mathrm{o}} A_{\mathrm{o}})^{r_{\mathrm{o}}}}{r_{\mathrm{o}}!} e^{-A_{\mathrm{o}}\lambda_{\mathrm{o}}} \quad r_{\mathrm{o}} = 0, 1, \ldots$$

where R_{o} is the number of clients outside. A_{o} is the area of the complimentary of target region. λ_{o} is a Poisson intensity parameter. The inference task is to estimate occupancy based on the power matrix $\underline{\mathbf{P}}$.

3 ESTIMATION SCHEMES

3.1 Bayes Estimation

We assume the Poisson intensity parameters λ_t and λ_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 $\underline{\mathbf{P}}$

$$\begin{aligned}\Pr\left(R_\mathrm{t} = r_\mathrm{t} | \underline{\mathbf{P}} = \underline{\mathbf{p}}\right) &= \int_{\{\underline{\mathbf{u}}:R_\mathrm{t}(\underline{\mathbf{u}})=r_\mathrm{t}, R_\mathrm{o}(\underline{\mathbf{u}})=r_\mathrm{o}\}} f_{\underline{\mathbf{U}}|\underline{\mathbf{P}}}\left(\underline{\mathbf{u}}|\underline{\mathbf{p}}\right) d\underline{\mathbf{u}} \\ &= \int_{\{\underline{\mathbf{u}}:R_\mathrm{t}(\underline{\mathbf{u}})=r_\mathrm{t}, R_\mathrm{o}(\underline{\mathbf{u}})=r_\mathrm{o}\}} \frac{f_{\underline{\mathbf{P}}|\underline{\mathbf{U}}}\left(\underline{\mathbf{p}}|\underline{\mathbf{u}}\right) f_{\underline{\mathbf{U}}}(\underline{\mathbf{u}})}{f_{\underline{\mathbf{P}}}\left(\underline{\mathbf{p}}\right)} d\underline{\mathbf{u}}.\end{aligned} \tag{3.1}$$

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

$$\begin{aligned} f_{\underline{\mathbf{U}}}(\underline{\mathbf{u}}) &= \frac{1}{A_\mathrm{t}^{R_\mathrm{t}(\underline{\mathbf{u}})}} \frac{(\lambda_\mathrm{t} A_\mathrm{t})^{R_\mathrm{t}(\underline{\mathbf{u}})}}{(R_\mathrm{t}(\underline{\mathbf{u}}))!} e^{-A_\mathrm{t}\lambda_\mathrm{t}} \\ &\quad \frac{1}{A_\mathrm{o}^{R_\mathrm{o}(\underline{\mathbf{u}})}} \frac{(\lambda_\mathrm{o} A_\mathrm{o})^{R_\mathrm{o}(\underline{\mathbf{u}})}}{(R_\mathrm{o}(\underline{\mathbf{u}}))!} e^{-A_\mathrm{o}\lambda_\mathrm{o}} \\ &= \frac{\lambda_\mathrm{t}^{R_\mathrm{t}(\underline{\mathbf{u}})}}{(R_\mathrm{t}(\underline{\mathbf{u}}))!} \frac{\lambda_\mathrm{o}^{R_\mathrm{o}(\underline{\mathbf{u}})}}{(R_\mathrm{o}(\underline{\mathbf{u}}))!} e^{-A_\mathrm{t}\lambda_\mathrm{t} - A_\mathrm{o}\lambda_\mathrm{o}}. \end{aligned} \tag{3.2}$$

The distribution of the received power vector $\mathbf{P}_j$ given a specific location $\mathbf{u}_j$ is equal to

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

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

$$f_{\underline{\mathbf{P}}|\underline{\mathbf{U}}}\left(\underline{\mathbf{p}}|\underline{\mathbf{u}}\right) = \prod_{j=1}^{n_\mathrm{a}} f_{\mathbf{P}_j|\mathbf{U}_j}(\mathbf{p}_j|\mathbf{u}_j). \tag{3.4}$$

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 $\underline{\mathbf{P}}$,

$$\begin{aligned} f_{\underline{\mathbf{P}}}\left(\underline{\mathbf{p}}\right) &= \int_{\{\underline{\mathbf{u}}:R_{\mathrm{t}}(\underline{\mathbf{u}})+R_{\mathrm{o}}(\underline{\mathbf{u}})=n_{\mathrm{a}}\}} f_{\underline{\mathbf{P}}|\underline{\mathbf{U}}}\left(\underline{\mathbf{p}}|\underline{\mathbf{u}}\right) f_{\underline{\mathbf{U}}}(\underline{\mathbf{u}})d\underline{\mathbf{u}} \\ &= \sum_{(r_{\mathrm{t}},r_{\mathrm{o}}):r_{\mathrm{t}}+r_{\mathrm{o}}=n_{\mathrm{a}}} \sum_{\{\mathbb{I}\subset[n_{\mathrm{a}}]:|\mathbb{I}|=r_{\mathrm{t}}\}} \frac{\lambda_{\mathrm{t}}^{r_{\mathrm{t}}}\lambda_{\mathrm{o}}^{r_{\mathrm{o}}}}{r_{\mathrm{t}}!r_{\mathrm{o}}!} e^{-A_{\mathrm{t}}\lambda_{\mathrm{t}}-A_{\mathrm{o}}\lambda_{\mathrm{o}}} \prod_{j\in\mathbb{I}} \mathscr{I}_{\mathscr{A}_{\mathrm{t}}}(j) \prod_{j\in\mathbb{I}^{\mathrm{c}}} \mathscr{I}_{\mathscr{A}_{\mathrm{o}}}(j). \end{aligned} \tag{3.5}$$

where the integral components are equal to

$$\mathscr{I}_{\mathscr{A}_{\mathrm{t}}}(j) = \int_{\mathscr{A}_{\mathrm{t}}} f_{\mathbf{P}_j|\mathbf{U}_j}(\mathbf{p}_j|\mathbf{u}_j)d\mathbf{u}_j \tag{3.6}$$

$$\mathscr{I}_{\mathscr{A}_{\mathrm{o}}}(j) = \int_{\mathscr{A}_{\mathrm{o}}} f_{\mathbf{P}_j|\mathbf{U}_j}(\mathbf{p}_j|\mathbf{u}_j)d\mathbf{u}_j. \tag{3.7}$$

Now, we can compute the posterior distribution of R_{t} given $\underline{\mathbf{P}}$ by substituting (3.2), (3.4), (3.5) into (3.1).

Thus, the Bayes estimator becomes

$$\begin{aligned} \hat{R}_{\mathrm{t}}\left(\underline{\mathbf{p}}\right) &= \mathrm{E}\left[R_{\mathrm{t}}|\underline{\mathbf{P}} = \underline{\mathbf{p}}\right] \\ &= \sum_{r_{\mathrm{t}}=0}^{n_{\mathrm{a}}} r_{\mathrm{t}} \Pr\left(R_{\mathrm{t}} = r_{\mathrm{t}}|\underline{\mathbf{P}} = \underline{\mathbf{p}}\right). \end{aligned} \tag{3.8}$$

3.2 Maximum likelihood estimation

In this section, we assume the Poisson intensity parameters λ_{t} and λ_{o} are unknown. Under this assumption, the distribution of $\underline{\mathbf{U}}$ can be written as

$$f_{\underline{\mathbf{U}}}(\underline{\mathbf{u}};\lambda_{\mathrm{t}},\lambda_{\mathrm{o}}) = \frac{\lambda_{\mathrm{t}}^{R_{\mathrm{t}}(\underline{\mathbf{u}})}}{(R_{\mathrm{t}}(\underline{\mathbf{u}}))!} \frac{\lambda_{\mathrm{o}}^{R_{\mathrm{o}}(\underline{\mathbf{u}})}}{(R_{\mathrm{o}}(\underline{\mathbf{u}}))!} e^{-A_{\mathrm{t}}\lambda_{\mathrm{t}}-A_{\mathrm{o}}\lambda_{\mathrm{o}}}. \tag{3.9}$$

The likelihood function is a function with two parameters, λ_{t} and λ_{o}

$$\begin{aligned} \mathscr{L}\left(\lambda_{\mathrm{t}},\lambda_{\mathrm{o}};\underline{\mathbf{p}},\underline{\mathbf{u}}\right) &= f_{\underline{\mathbf{P}},\underline{\mathbf{U}}}\left(\underline{\mathbf{p}},\underline{\mathbf{u}};\lambda_{\mathrm{t}},\lambda_{\mathrm{o}}\right) \\ &= f_{\underline{\mathbf{P}}|\underline{\mathbf{U}}}\left(\underline{\mathbf{p}}|\underline{\mathbf{u}}\right) f_{\underline{\mathbf{U}}}(\underline{\mathbf{u}};\lambda_{\mathrm{t}},\lambda_{\mathrm{o}}). \end{aligned} \tag{3.10}$$

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

$$\begin{aligned}\mathscr{L}\left(\lambda_{\mathrm{t}},\lambda_{\mathrm{o}};\underline{\mathbf{p}}\right) &= \int_{\{\underline{\mathbf{u}}:R_{\mathrm{t}}(\underline{\mathbf{u}})+R_{\mathrm{o}}(\underline{\mathbf{u}})=n_{\mathrm{a}}\}} f_{\underline{\mathbf{P}}|\underline{\mathbf{U}}}\left(\underline{\mathbf{p}}|\underline{\mathbf{u}}\right) f_{\underline{\mathbf{U}}}\left(\underline{\mathbf{u}};\lambda_{\mathrm{t}},\lambda_{\mathrm{o}}\right) d\underline{\mathbf{u}} \\ &= e^{-A_{\mathrm{t}}\lambda_{\mathrm{t}}-A_{\mathrm{o}}\lambda_{\mathrm{o}}} \sum_{(r_{\mathrm{t}},r_{\mathrm{o}}):r_{\mathrm{t}}+r_{\mathrm{o}}=n_{\mathrm{a}}} \frac{\lambda_{\mathrm{t}}^{r_{\mathrm{t}}}\lambda_{\mathrm{o}}^{r_{\mathrm{o}}}}{r_{\mathrm{t}}!r_{\mathrm{o}}!} \sum_{\{\mathbb{I}\subset[n_{\mathrm{a}}]:|\mathbb{I}|=r_{\mathrm{t}}\}} \prod_{j\in\mathbb{I}} \mathscr{I}_{\mathscr{A}_{\mathrm{t}}}(j) \prod_{j\in\mathbb{I}^{\mathrm{c}}} \mathscr{I}_{\mathscr{A}_{\mathrm{o}}}(j).\end{aligned} \tag{3.11}$$

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

$$\max_{\lambda_{\mathrm{t}},\lambda_{\mathrm{o}}} \mathscr{L}\left(\lambda_{\mathrm{t}},\lambda_{\mathrm{o}};\underline{\mathbf{p}}\right) = \max_{\alpha} \mathscr{L}\left(\frac{n_{\mathrm{a}}}{A_{\mathrm{t}}}\alpha, \frac{n_{\mathrm{a}}}{A_{\mathrm{o}}}(1-\alpha);\underline{\mathbf{p}}\right) \tag{3.12}$$

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

$$\begin{aligned}&\mathscr{L}\left(\frac{n_{\mathrm{a}}}{A_{\mathrm{t}}}\alpha, \frac{n_{\mathrm{a}}}{A_{\mathrm{o}}}(1-\alpha);\underline{\mathbf{p}}\right) \\ &= \sum_{(r_{\mathrm{t}},r_{\mathrm{o}}):r_{\mathrm{t}}+r_{\mathrm{o}}=n_{\mathrm{a}}} \frac{e^{-n_{\mathrm{a}}}n_{\mathrm{a}}^{n_{\mathrm{a}}}}{r_{\mathrm{t}}!r_{\mathrm{o}}!} \left(\frac{\alpha}{A_{\mathrm{t}}}\right)^{r_{\mathrm{t}}} \left(\frac{1-\alpha}{A_{\mathrm{o}}}\right)^{r_{\mathrm{o}}} \\ &\quad \times \sum_{\{\mathbb{I}\subset[n_{\mathrm{a}}]:|\mathbb{I}|=r_{\mathrm{t}}\}} \prod_{j\in\mathbb{I}} \mathscr{I}_{\mathscr{A}_{\mathrm{t}}}(j) \prod_{j\in\mathbb{I}^{\mathrm{c}}} \mathscr{I}_{\mathscr{A}_{\mathrm{o}}}(j)\end{aligned} \tag{3.13}$$

Now, we can use numerical methods to get the values of λ_{t} and λ_{o} which maximize the likelihood function. Once λ_{t} and λ_{o} are obtained, the maximum likelihood estimator can be calculated as

$$\begin{aligned}\hat{R}_{\mathrm{t}}\left(\underline{\mathbf{p}}\right) &= \mathrm{E}_{\hat{\lambda}_{\mathrm{t}},\hat{\lambda}_{\mathrm{o}}}\left[R_{\mathrm{t}}|\underline{\mathbf{P}}=\underline{\mathbf{p}}\right] \\ &= \sum_{r_{\mathrm{t}}=0}^{n_{\mathrm{a}}} r_{\mathrm{t}} \Pr\left(R_{\mathrm{t}}=r_{\mathrm{t}}|\underline{\mathbf{P}}=\underline{\mathbf{p}};\hat{\lambda}_{\mathrm{t}},\hat{\lambda}_{\mathrm{o}}\right).\end{aligned} \tag{3.14}$$

4 NUMERICAL SIMULATION

5 EXPERIMENT IMPLEMENTATION

6 CONCLUSION

REFERENCES

[1] T. A. Nguyen and M. Aiello, "Energy intelligent buildings based on user activity: A survey," *Energy and Buildings*, vol. 56, pp. 244 – 257, 2013.

[2] B. Balaji, J. Xu, A. Nwokafor, R. Gupta, and Y. Agarwal, "Sentinel: Occupancy based hvac actuation using existing wifi infrastructure within commercial buildings," in *Proceedings of the 11th ACM Conference on Embedded Networked Sensor Systems*, SenSys '13, (New York, NY, USA), pp. 17:1–17:14, ACM, 2013.

[3] D. Valerio, A. D'Alconzo, F. Ricciato, and W. Wiedermann, "Exploiting cellular networks for road traffic estimation: A survey and a research roadmap," in *Vehicular Technology Conference, 2009. VTC Spring 2009. IEEE 69th*, pp. 1–5, April 2009.

[4] Cisco Systems, Inc., *Visual Networking Index: Global Mobile Data Traffic Forecast Update*, 2016.

[5] C. Xu, B. Firner, R. S. Moore, Y. Zhang, W. Trappe, R. Howard, F. Zhang, and N. An, "Scpl: Indoor device-free multi-subject counting and localization using radio signal strength," in *Proceedings of the 12th International Conference on Information Processing in Sensor Networks*, IPSN '13, (New York, NY, USA), pp. 79–90, ACM, 2013.

[6] M. Seifeldin, A. Saeed, A. E. Kosba, A. El-Keyi, and M. Youssef, "Nuzzer: A large-scale device-free passive localization system for wireless environments," *IEEE Transactions on Mobile Computing*, vol. 12, pp. 1321–1334, July 2013.

[7] eMarketer, Inc., *Worldwide Internet and Mobile Users: eMarketer's Updated Estimates for 2015*, 2015.

[8] comScore, *comScore Reports December 2015 U.S. Smartphone Subscriber Market Share*, 2015.

[9] T. S. Rappaport *et al.*, *Wireless communications: principles and practice*, vol. 2. Prentice Hall PTR New Jersey, 1996.

[10] H. L. Bertoni, *Radio propagation for modern wireless systems*. Pearson Education, 1999.

[11] G. L. Stüber, *Principles of mobile communication*. Springer Science & Business Media, 2011.

[12] Z. Ma and A. B. Chan, "Crossing the line: Crowd counting by integer programming with local features," in *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2013.

[13] Y. Taniguchi, M. Mizushima, G. Hasegawa, H. Nakano, and M. Matsuoka, "Counting pedestrians passing through a line in crowded scenes by extracting optical flows," *International Information Institute (Tokyo).Information*, vol. 19, pp. 303–316, 01 2016.

Copyright - Copyright International Information Institute Jan 2016; Document feature - Illustrations; Equations; Tables; Graphs; ; Last updated - 2016-07-30.

[14] M. Li, Z. Zhang, K. Huang, and T. Tan, "Estimating the number of people in crowded scenes by mid based foreground segmentation and head-shoulder detection," in *Pattern Recognition, 2008. ICPR 2008. 19th International Conference on*, pp. 1–4, IEEE, 2008.

[15] V. Garg and N. Bansal, "Smart occupancy sensors to reduce energy consumption," *Energy and Buildings*, vol. 32, no. 1, pp. 81 – 87, 2000.

[16] O. Shih and A. Rowe, "Occupancy estimation using ultrasonic chirps," in *Proceedings of the ACM/IEEE Sixth International Conference on Cyber-Physical Systems*, ICCPS '15, (New York, NY, USA), pp. 149–158, ACM, 2015.

[17] Nishide, R., and H. Takada, "Exploring efficient methods to extract pedestrian flows on a mobile adhoc network," *The 6th International Conference on Mobile Ubiquitous Computing, Systems, Services and Technologies*, 2012.

[18] Depatla, Saandeep, Arjun Muralidharan, and Yasamin Mostofi, "Occupancy estimation using only wifi power measurements," *IEEE Journal on Selected Areas in Communications*, vol. 33, pp. 1381–1393, 05 2015.

[19] N. Abedi, A. Bhaskar, and E. Chung, "Bluetooth and wi-fi mac address based crowd data collection and monitoring : benefits, challenges and enhancement," in *36th Aus-*

tralasian Transport Research Forum (ATRF), (Queensland University of Technology, Brisbane, QLD), October 2013.

[20] W. Xi, J. Zhao, X. Y. Li, K. Zhao, S. Tang, X. Liu, and Z. Jiang, “Electronic frog eye: Counting crowd using wifi,” in *IEEE INFOCOM 2014 - IEEE Conference on Computer Communications*, pp. 361–369, April 2014.

[21] S. Depatla, A. Muralidharan, and Y. Mostofi, “Occupancy estimation using only wifi power measurements,” *IEEE Journal on Selected Areas in Communications*, vol. 33, pp. 1381–1393, July 2015.

[22] D. Zwillinger, “Crc standard mathematical tables and formulae,” 1995.