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 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 [3]. 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, as well as occupancy estimation.

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 [5, 6, 7]. 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 [8], 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 [9], 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 [10] and Wi-Fi [11]. However, the short transmission range limits the performance of Bluetooth-based methods. A research compared Wi-Fi and Bluetooth approaches [12]. 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 [13], the author proposes FCC, a device-Free Crowd Counting approach based on channel state information measurements. In [14], 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 paper, 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 paper 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 PROBLEM FORMULATION

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 $\mathscr{A}_\mathrm{t}$ to represent the target area and $\mathscr{A}_\mathrm{o}$ 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

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

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

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