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 device in a certain area based on monitoring and processing Wi-Fi metadata. 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.

1 INTRODUCTION

The number of Wi-Fi access points and the number of Wi-Fi client devices have been increasing dramatically in recent years. 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 [1]. Modern smartphones 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.

In the research, we focus on occupancy estimation based on Wi-Fi packets and we analyze the benefits associated with using directional antennas. We introduce a Bayes estimation algorithm and a maximum likelihood scheme to estimate occupancy. We employ numerical simulations to compare the performance corresponding to sensing devices with directional antennas and isotropic antennas. In addition, our findings are further supported through field 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 proposal is organized as follows. In Section 2, we describe related work. In Section 3, we introduce a formal problem formulation. In Section 4, we propose two estimation schemes. These schemes are evaluated through numerical simulations in Section 5. We then discuss experimental result, along with description of experiment setup. Finally, we offer concluding remarks in the last section.

2 RELATED WORK

There have been many research initiatives focusing on occupancy estimation. Generally speaking, they are based either on images, videos, or RF signals. Approaches based on camera use captured images to estimate the number of people in a crowded scene [2, 3]. 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. Other approaches based on RF signals attracted a lot of attention recently. Several methods are based on Bluetooth [4] or Wi-Fi signals [5]. However, the short transmission range limits the performance of Bluetooth-based methods. A research compared Wi-Fi and Bluetooth approaches. 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 [6]. 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.

3 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.

$$\underline{\mathbf{U}} = (\mathbf{U}_1, \ldots, \mathbf{U}_{n_\mathrm{a}}). \tag{3.1}$$

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

$$P_{ij}[\mathrm{dBm}] = A + B\log_{10}(d_{ij}) + L_{ij} + G_i(\phi_{ij}) \tag{3.2}$$

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

$$f_{L_{ij}}(\ell) = \frac{1}{\sqrt{2\pi}\sigma_{\mathrm{s}}} \exp\left(-\frac{\ell^2}{2\sigma_{\mathrm{s}}^2}\right) \tag{3.3}$$

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 $\underline{\mathbf{P}}$.

4 ESTIMATION SCHEMES

4.1 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 $\underline{\mathbf{P}}$

$$\begin{aligned}\Pr\left(R_{\mathrm{t}}=r_{\mathrm{t}}|\underline{\mathbf{P}}=\underline{\mathbf{p}}\right) &= \int_{\{\underline{\mathbf{u}}:R_{\mathrm{t}}(\underline{\mathbf{u}})=r_{\mathrm{t}},R_{\mathrm{o}}(\underline{\mathbf{u}})=r_{\mathrm{o}}\}} f_{\underline{\mathbf{U}}|\underline{\mathbf{P}}}\left(\underline{\mathbf{u}}|\underline{\mathbf{p}}\right)d\underline{\mathbf{u}} \\ &= \int_{\{\underline{\mathbf{u}}:R_{\mathrm{t}}(\underline{\mathbf{u}})=r_{\mathrm{t}},R_{\mathrm{o}}(\underline{\mathbf{u}})=r_{\mathrm{o}}\}} \frac{f_{\underline{\mathbf{P}}|\underline{\mathbf{U}}}\left(\underline{\mathbf{p}}|\underline{\mathbf{u}}\right)f_{\underline{\mathbf{U}}}(\underline{\mathbf{u}})}{f_{\underline{\mathbf{P}}}\left(\underline{\mathbf{p}}\right)}d\underline{\mathbf{u}}.\end{aligned} \tag{4.1}$$

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

$$\begin{aligned}f_{\underline{\mathbf{U}}}(\underline{\mathbf{u}}) &= \frac{1}{A_{\mathrm{t}}^{R_{\mathrm{t}}(\underline{\mathbf{u}})}}\frac{(\lambda_{\mathrm{t}}A_{\mathrm{t}})^{R_{\mathrm{t}}(\underline{\mathbf{u}})}}{(R_{\mathrm{t}}(\underline{\mathbf{u}}))!}e^{-A_{\mathrm{t}}\lambda_{\mathrm{t}}} \\ &\frac{1}{A_{\mathrm{o}}^{R_{\mathrm{o}}(\underline{\mathbf{u}})}}\frac{(\lambda_{\mathrm{o}}A_{\mathrm{o}})^{R_{\mathrm{o}}(\underline{\mathbf{u}})}}{(R_{\mathrm{o}}(\underline{\mathbf{u}}))!}e^{-A_{\mathrm{o}}\lambda_{\mathrm{o}}} \\ &= \frac{\lambda_{\mathrm{t}}^{R_{\mathrm{t}}(\underline{\mathbf{u}})}}{(R_{\mathrm{t}}(\underline{\mathbf{u}}))!}\frac{\lambda_{\mathrm{o}}^{R_{\mathrm{o}}(\underline{\mathbf{u}})}}{(R_{\mathrm{o}}(\underline{\mathbf{u}}))!}e^{-A_{\mathrm{t}}\lambda_{\mathrm{t}}-A_{\mathrm{o}}\lambda_{\mathrm{o}}}.\end{aligned} \tag{4.2}$$

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

$$\begin{aligned}f_{\mathbf{P}_j|\mathbf{U}_j}(\mathbf{p}_j|\mathbf{u}_j) &= \prod_{i=1}^{n_{\mathrm{s}}} f_{L_{ij}}(p_{ij}-A-B\log_{10}(d_{ij})-G_i(\phi_{ij})) \\ &= \frac{1}{(2\pi\sigma_{\mathrm{s}}^2)^{\frac{n_{\mathrm{s}}}{2}}}\prod_{i=1}^{n_{\mathrm{s}}} e^{-\frac{(p_{ij}-A-B\log_{10}(d_{ij})-G_i(\phi_{ij}))^2}{2\sigma_{\mathrm{s}}^2}} \\ &= \left(2\pi\sigma_{\mathrm{s}}^2\right)^{-\frac{n_{\mathrm{s}}}{2}} e^{-\frac{\sum_{i=1}^{n_{\mathrm{s}}}(p_{ij}-A-B\log_{10}(d_{ij})-G_i(\phi_{ij}))^2}{2\sigma_{\mathrm{s}}^2}}.\end{aligned} \tag{4.3}$$

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

$$f_{\underline{\mathbf{P}}|\underline{\mathbf{U}}}\left(\underline{\mathbf{p}}|\underline{\mathbf{u}}\right) = \prod_{j=1}^{n_{\mathrm{a}}} f_{\mathbf{P}_j|\mathbf{U}_j}(\mathbf{p}_j|\mathbf{u}_j). \tag{4.4}$$

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

$$\begin{aligned} f_{\underline{\mathbf{P}}}\left(\underline{\mathbf{p}}\right) &= \int_{\{\underline{\mathbf{u}}:R_{\mathrm{t}}(\underline{\mathbf{u}})+R_{\mathrm{o}}(\underline{\mathbf{u}})=n_{\mathrm{a}}\}} f_{\underline{\mathbf{P}}|\underline{\mathbf{U}}}\left(\underline{\mathbf{p}}|\underline{\mathbf{u}}\right) f_{\underline{\mathbf{U}}}(\underline{\mathbf{u}})d\underline{\mathbf{u}} \\ &= \sum_{(r_{\mathrm{t}},r_{\mathrm{o}}):r_{\mathrm{t}}+r_{\mathrm{o}}=n_{\mathrm{a}}} \sum_{\{\mathbb{I}\subset[n_{\mathrm{a}}]:|\mathbb{I}|=r_{\mathrm{t}}\}} \frac{\lambda_{\mathrm{t}}^{r_{\mathrm{t}}}\lambda_{\mathrm{o}}^{r_{\mathrm{o}}}}{r_{\mathrm{t}}!r_{\mathrm{o}}!} e^{-A_{\mathrm{t}}\lambda_{\mathrm{t}}-A_{\mathrm{o}}\lambda_{\mathrm{o}}} \prod_{j\in\mathbb{I}} \mathscr{I}_{\mathscr{A}_{\mathrm{t}}}(j) \prod_{j\in\mathbb{I}^{\mathrm{c}}} \mathscr{I}_{\mathscr{A}_{\mathrm{o}}}(j). \end{aligned} \tag{4.5}$$

where the integral components are equal to

$$\mathscr{I}_{\mathscr{A}_{\mathrm{t}}}(j) = \int_{\mathscr{A}_{\mathrm{t}}} f_{\mathbf{P}_j|\mathbf{U}_j}(\mathbf{p}_j|\mathbf{u}_j)d\mathbf{u}_j \tag{4.6}$$

$$\mathscr{I}_{\mathscr{A}_{\mathrm{o}}}(j) = \int_{\mathscr{A}_{\mathrm{o}}} f_{\mathbf{P}_j|\mathbf{U}_j}(\mathbf{p}_j|\mathbf{u}_j)d\mathbf{u}_j. \tag{4.7}$$

Now, we can compute the posterior distribution of R_{t} given $\underline{\mathbf{P}}$ by substituting (4.2), (4.4), (4.5) into (4.1).

Thus, the Bayes estimator becomes

$$\begin{aligned} \hat{R}_{\mathrm{t}}\left(\underline{\mathbf{p}}\right) &= \mathrm{E}\left[R_{\mathrm{t}}|\underline{\mathbf{P}} = \underline{\mathbf{p}}\right] \\ &= \sum_{r_{\mathrm{t}}=0}^{n_{\mathrm{a}}} r_{\mathrm{t}} \Pr\left(R_{\mathrm{t}} = r_{\mathrm{t}}|\underline{\mathbf{P}} = \underline{\mathbf{p}}\right). \end{aligned} \tag{4.8}$$

4.2 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

$$f_{\underline{\mathbf{U}}}(\underline{\mathbf{u}};\lambda_{\mathrm{t}},\lambda_{\mathrm{o}}) = \frac{\lambda_{\mathrm{t}}^{R_{\mathrm{t}}(\underline{\mathbf{u}})}}{(R_{\mathrm{t}}(\underline{\mathbf{u}}))!} \frac{\lambda_{\mathrm{o}}^{R_{\mathrm{o}}(\underline{\mathbf{u}})}}{(R_{\mathrm{o}}(\underline{\mathbf{u}}))!} e^{-A_{\mathrm{t}}\lambda_{\mathrm{t}}-A_{\mathrm{o}}\lambda_{\mathrm{o}}}. \tag{4.9}$$

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

$$\begin{aligned} \mathscr{L}\left(\lambda_{\mathrm{t}},\lambda_{\mathrm{o}};\underline{\mathbf{p}},\underline{\mathbf{u}}\right) &= f_{\underline{\mathbf{P}},\underline{\mathbf{U}}}\left(\underline{\mathbf{p}},\underline{\mathbf{u}};\lambda_{\mathrm{t}},\lambda_{\mathrm{o}}\right) \\ &= f_{\underline{\mathbf{P}}|\underline{\mathbf{U}}}\left(\underline{\mathbf{p}}|\underline{\mathbf{u}}\right) f_{\underline{\mathbf{U}}}(\underline{\mathbf{u}};\lambda_{\mathrm{t}},\lambda_{\mathrm{o}}). \end{aligned} \tag{4.10}$$

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

$$\begin{aligned}\mathscr{L}\left(\lambda_{\mathrm{t}},\lambda_{\mathrm{o}};\underline{\mathbf{p}}\right) &= \int_{\{\underline{\mathbf{u}}:R_{\mathrm{t}}(\underline{\mathbf{u}})+R_{\mathrm{o}}(\underline{\mathbf{u}})=n_{\mathrm{a}}\}} f_{\underline{\mathbf{P}}|\underline{\mathbf{U}}}\left(\underline{\mathbf{p}}|\underline{\mathbf{u}}\right) f_{\underline{\mathbf{U}}}\left(\underline{\mathbf{u}};\lambda_{\mathrm{t}},\lambda_{\mathrm{o}}\right) d\underline{\mathbf{u}} \\ &= e^{-A_{\mathrm{t}}\lambda_{\mathrm{t}}-A_{\mathrm{o}}\lambda_{\mathrm{o}}} \sum_{(r_{\mathrm{t}},r_{\mathrm{o}}):r_{\mathrm{t}}+r_{\mathrm{o}}=n_{\mathrm{a}}} \frac{\lambda_{\mathrm{t}}^{r_{\mathrm{t}}}\lambda_{\mathrm{o}}^{r_{\mathrm{o}}}}{r_{\mathrm{t}}!r_{\mathrm{o}}!} \sum_{\{\mathbb{I}\subset[n_{\mathrm{a}}]:|\mathbb{I}|=r_{\mathrm{t}}\}} \prod_{j\in\mathbb{I}} \mathscr{I}_{\mathscr{A}_{\mathrm{t}}}(j) \prod_{j\in\mathbb{I}^{\mathrm{c}}} \mathscr{I}_{\mathscr{A}_{\mathrm{o}}}(j).\end{aligned} \tag{4.11}$$

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

$$\max_{\lambda_{\mathrm{t}},\lambda_{\mathrm{o}}} \mathscr{L}\left(\lambda_{\mathrm{t}},\lambda_{\mathrm{o}};\underline{\mathbf{p}}\right) = \max_{\alpha} \mathscr{L}\left(\frac{n_{\mathrm{a}}}{A_{\mathrm{t}}}\alpha, \frac{n_{\mathrm{a}}}{A_{\mathrm{o}}}(1-\alpha);\underline{\mathbf{p}}\right) \tag{4.12}$$

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

$$\begin{aligned}&\mathscr{L}\left(\frac{n_{\mathrm{a}}}{A_{\mathrm{t}}}\alpha, \frac{n_{\mathrm{a}}}{A_{\mathrm{o}}}(1-\alpha);\underline{\mathbf{p}}\right) \\ &= \sum_{(r_{\mathrm{t}},r_{\mathrm{o}}):r_{\mathrm{t}}+r_{\mathrm{o}}=n_{\mathrm{a}}} \frac{e^{-n_{\mathrm{a}}}n_{\mathrm{a}}^{n_{\mathrm{a}}}}{r_{\mathrm{t}}!r_{\mathrm{o}}!} \left(\frac{\alpha}{A_{\mathrm{t}}}\right)^{r_{\mathrm{t}}} \left(\frac{1-\alpha}{A_{\mathrm{o}}}\right)^{r_{\mathrm{o}}} \\ &\quad \times \sum_{\{\mathbb{I}\subset[n_{\mathrm{a}}]:|\mathbb{I}|=r_{\mathrm{t}}\}} \prod_{j\in\mathbb{I}} \mathscr{I}_{\mathscr{A}_{\mathrm{t}}}(j) \prod_{j\in\mathbb{I}^{\mathrm{c}}} \mathscr{I}_{\mathscr{A}_{\mathrm{o}}}(j)\end{aligned} \tag{4.13}$$

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

$$\begin{aligned}\hat{R}_{\mathrm{t}}\left(\underline{\mathbf{p}}\right) &= \mathrm{E}_{\hat{\lambda}_{\mathrm{t}},\hat{\lambda}_{\mathrm{o}}}\left[R_{\mathrm{t}}|\underline{\mathbf{P}}=\underline{\mathbf{p}}\right] \\ &= \sum_{r_{\mathrm{t}}=0}^{n_{\mathrm{a}}} r_{\mathrm{t}} \Pr\left(R_{\mathrm{t}}=r_{\mathrm{t}}|\underline{\mathbf{P}}=\underline{\mathbf{p}};\hat{\lambda}_{\mathrm{t}},\hat{\lambda}_{\mathrm{o}}\right).\end{aligned} \tag{4.14}$$

5 Conclusion

This work will include a numerical simulation corresponding to two estimation schemes. The simulation code is written in python. The simulation will show the performance comparison between directional antenna and isotropic antenna. The performance is evaluated via estimation error(BMSE for Bayesian estimation and MSE for maximum likelihood estimation). Preliminary results shows that performance improved when using directional antennas. To further support this result, an experiment will be conducted in the line of sight areas to obtain the experimental data. The performance of estimation will be reported with the experimental data obtained.

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