Finding by Counting: A Packet Count Based Indoor Localization Technique using BLE Sensors

Subham De
University of Illinois at Urbana-Champaign
Urbana, Illinois 61801
de5@illinois.edu

Robin Kravets
University of Illinois at Urbana-Champaign
Urbana, Illinois 61801
rhk@illinois.edu

Hari Sundaram
University of Illinois at Urbana-Champaign
Urbana, Illinois 61801
hs1@illinois.edu

ABSTRACT

We have developed a probabilistic packet reception rate model based technique for localization in indoor environments. We use Bluetooth Low Energy beacons as anchor nodes and count the packets sent out by these devices to localize a moving person. Due to unreliability and randomness in received signal strength (RSS) values measured in a dynamic indoor environment, we decided on using packet counts instead i.e number of packets received from a device. We model the probability of reception of a packet as a generalized quadratic function of distance, beacon power and advertising frequency. Then, we use a Bayesian formulation to determine the coefficients of the packet count model using small set of empirical observations from the environment. We use an augmented particle filter technique incorporating packet count model to track a moving person. Our approach has average localization error of $\sim 1.2m$ [3] in two different environments - a retail store and a library.

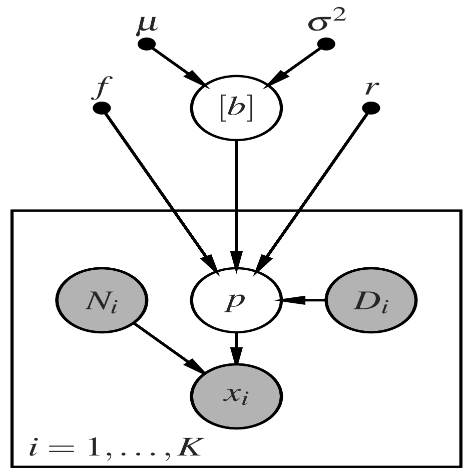

Figure 1: Parameters [b] unknown/hidden in training phase. D_i unknown in localization phase.

1 RELATED WORK

A wide range of techniques exist to localize a node within an indoor environment which can broadly classified to 2 types — range-based and range free. RADAR [1] , Horus [6] , EZ [2] , Zee [5] are some state-of-art range-based techniques. RADAR, Horus and Zee use WiFi fingerprints while EZ uses a log distance path loss model. All of these methods use RSS value to map distance. MCL [4] , MSL are range-free techniques that assume that a heard beacon must be within a threshold distance to the current measurement location. Our framework does not calculate RSS loss for each packet, or make any assumptions about beacon hearability distance. Instead, we model the probability of receiving a packet to localize.

2 METHODOLOGY

We assume that we are in a $W \times L$ space with K BLE beacons in fixed, known positions in the space. We use Bluvision iBeeks as beacons. All iBeeks transmit at the same frequency f and at the same power r. The probability of receiving packets from any beacon is binomially distributed with parameter p. The packets are received by a Texas Instrument Packet Sniffer which is a CC2540 dongle and connected to a laptop. iBeeks send out packets in different channels which affects packet properties a lot. We use TI sniffer as it automatically filters packets on one advertising channel. When an individual moves through the space with the laptop, the sniffer logs the received BLE packets on basis of which we track the individual every δ sec.

2.1 Model Estimation

We discover how p, the probability that we would hear a packet from a beacon varies as a function g of distance (d), frequency (f) and Power (r). We assume the functional form

$$\log p = g(d, f, r) = b_0 + \sum_i b_i x_i + \sum_{i,j} b_{i,j} x_i x_j, \quad i, j \in \{1, 2, 3\} \quad (1)$$

where, x_i refer to the variables of d, f, r. We estimate $\theta \equiv \{b_i\}$ with empirical data - number of packets heard from every beacon at few known locations. Assume that we are at a particular spot A, listening to N packets sent from i-th beacon. Then the number of packets received c_i is drawn from a binomial distribution:

$$c_i = B(N, p_i) \quad (2)$$

$$p_i = g(f, r, d_{i,A}) \quad (3)$$

$d_{i,A}$ is the distance between the spot A and the location l_i of the i-th beacon. We assume that the prior of each of the coefficients b_i is drawn from i.i.d normal distribution $b_i \sim \mathcal{N}(\mu, \sigma)$ The Bayesian formulation is compactly summarized in Figure 1. We compute the posterior $P(\theta)$ using a Markov Chain Monte Carlo technique.

2.2 Localization

While user walks, we assume the collection of a received packet log $L = \{(b_1, t_1), (b_2, t_2), \ldots, (b_N, t_N)\}$ where b_i refers to the BLE beacon id heard at time t_i. The goal is to determine a list of N locations $XY_\delta = \{x_i, y_i; \delta\}$, at a time resolution δ. We use augmented particle filter approach.

$$
\begin{aligned}
s_i &\sim U(0, S_{max}),\ i \in \{1, \ldots, N-1\}\\
x_0 &\sim U(0, W),\\
y_0 &\sim U(0, L),\\
x_i \mid x_{i-1} &\sim \mathcal{N}(0, s_{i-1} * \delta),\ i \in \{1, \ldots, N-1\}\\
y_i \mid y_{i-1} &\sim \mathcal{N}(0, s_{i-1} * \delta), i \in \{1, \ldots, N-1\}\\
c_{i,k} &= B(M, p_{i,k}),\ M = f * \delta,\\
p_{i,k} &= g\left(f, r, d_{i,k}\right),\\
d_{i,k} &= \sqrt{(x_i - l_{k,x})^2 + (y_i - l_{k,y})^2}.
\end{aligned}
$$

where s_i is the speed while moving from the i-th location. S_{max} is the maximum possible moving speed. (x_i, y_i) is the location at i-th time interval. $c_{i,k}$ is the number of packets heard from k-th beacon at i-th time interval. It is Binomially distributed with $p_{i,k}$. U refers to uniform while N refers to normal distribution.

3 EVALUATION

We conducted experimental studies in two different academic library space environments. We collect data at three values each for device parameters of frequency and power. We use frequency values of 1Hz, 2Hz and 10Hz. We set beacon powers at values -20db, -15db, -12db. Taking the mean estimates of the posterior distributions of each parameter, we have the model as:

$$\log p = -0.101 - 0.012f + 0.056r - 0.272d + 0.189rd$$

The mean of the other coefficients are close to zero and ignored. Figure 2 shows the model fit. The dots show the raw packet counts received at varying distance while the curves represent the Bayesian fit. We can see from the figure that increasing power increases the packet reception probability and that *decreasing* frequency *increases* packet reception due to decreasing packet interference.

Localization Accuracy : We have compared against MCL [4] to see the effects of the packet reception model on its performance. We term our localization framework as Packet Count-Monte-Carlo Localization or PC-MCL in short. Table 1 shows the average error for different device settings.

4 ONGOING WORK

The initial version of Finding by Counting system has a few limitations — lack of auto-configuration of beacon infrastructure, finding out optimal placement of beacons. We placed the beacons at fixed spots and manually noted down their location information. Now if the localization area is large and demands greater number of beacons, overhead of deployment becomes high. Also in our initial set-up we placed beacons in a grid. We did not optimize placements for best accuracy results. We are developing Finding By Counting 2.0 that addresses both the problems. We are testing it out in a local retail store. The advanced version automatically finds the location of bulk of devices based on a small set of master beacons with known location. Also given a budget constraint of max K devices, it optimally places them to achieve best accuracy.

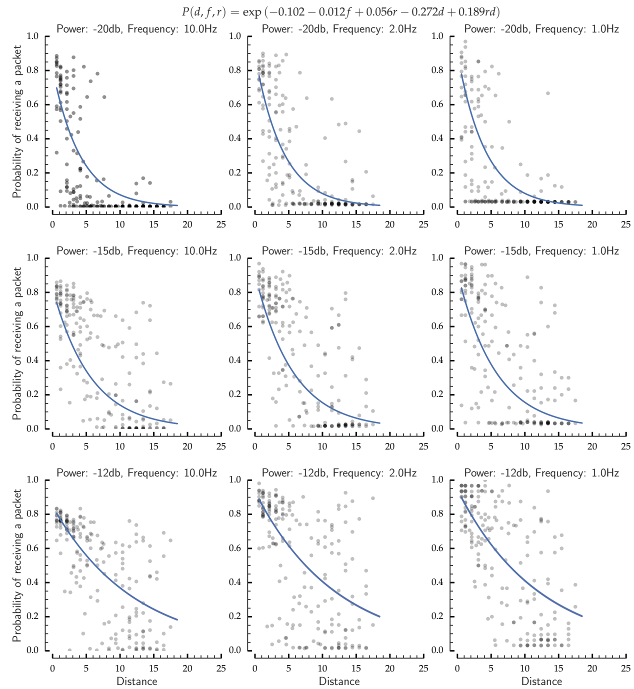

Figure 2: The figure show the generalized linear model fit to changing values of frequency and power.

Power	Frequency	PC-MCL error (m)	MCL error (m)
-20dB	2 Hz	1.99 (↓ 40.2%)	3.33
-20dB	1 Hz	1.83 (↓ 45.4%)	3.35
-15dB	10 Hz	1.11 (↓ 65.3%)	3.20
-15dB	2 Hz	1.48 (↓ 53.3%)	3.17
-15dB	1 Hz	1.39 (↓ 57.9%)	3.30
-12dB	2 Hz	1.56 (↓ 54.1%)	3.40
-12dB	1 Hz	1.49 (↓ 54.8%)	3.30

Table 1: Average estimation error in meters for the proposed Packet Count-MCL against the standard MCL. The PC-MCL error varies in range $1 - 2m$, while the standard MCL error is always over $3m$. Error is least for $-15dB$ power. In a sense, $-15db$ is "just right": $-20dB$ has low beacon coverage of physical space and $-12dB$ increases confusion with high coverage.

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