Occupancy Analytics in Retail Stores Using Wireless Signals

Saandeep Depatla
Uber Inc., USA
saandeep@uber.com

Yasamin Mostofi
Department of Electrical and Computer Engineering
University of California Santa Barbara, Santa Barbara, USA
ymostofi@ece.ucsb.edu

***Abstract*—In this paper, we propose a new framework to estimate the occupancy dynamics of the shoppers over a whole retail store, based on the received power measurements of wireless links that are installed in only a small number of aisles, and without relying on people to carry any device. More specifically, we utilize the received power measurements collected by a small number of wireless links installed in only a few aisles of a retail store and show that we can estimate the rate of arrival of people in all the aisles of the retail store. We first show how a pair of wireless links in an aisle can estimate the rate of arrival of people into that aisle for the general case where people can have a bi-directional flow. We then propose a new framework to estimate the rate of arrival of people into all the aisles of the retail store, using the received power measurements of a number of wireless links that are installed in only a few aisles. Our proposed approach utilizes the sparsity in the spatial and temporal gradient of the occupancy dynamics and poses an optimization problem to estimate the arrival rates over the whole store based only on a very small number of wireless measurements. We thoroughly validate our framework with several experiments in three different retail stores - Kmart and two anonymous retail stores (Store-2 and Store-3), using the RSSI measurements of Bluetooth Low Energy (BLE) Chips. Our results confirm that our framework can accurately estimate the rate of arrival of people into different aisles of a retail store with minimal wireless sensing. More specifically, we show that our approach can estimate the rate of arrival of people in different aisles of a store, with an average root mean square of 0.03 people/minute, when averaged over all the aisles and all the time, and while reducing the number of required wireless links by 57%.**

I. Introduction

In recent years, there has been an increased interest in estimating the number of people a given area. Occupancy estimation has several potential applications. For instance, in places like retail stores, popular aisles in the store can be identified which can help the store plan the services better [1]. In smart buildings, heating and cooling can be automatically adjusted based on the occupancy level, which can help improve the energy efficiency [2]. In smart cities, occupancy estimation can help in planning the traffic [3].

In the literature, several methods have been proposed to estimate the occupancy in an area. They can be classified into four different categories as follows:

1) Vision-based sensing: These methods employ cameras and process the video to estimate the occupancy in a given area [4]–[7]. However, in places like retail stores, vision-based methods pose serious privacy concerns. For instance, a recent survey on retail shoppers revealed that 75% of the people who understood the capabilities of vision-based tracking technologies found it intrusive to track their behavior using cameras [8]. Furthermore, employing such tracking techniques could lead to shoppers not visiting the corresponding stores [9].

Fig. 1: A large retail store with several aisles. Our objective is to estimate the rate of arrival of people into all the aisles throughout the store, based on sensing with wireless links that are only installed in a few aisles. Image courtesy: Thebricspost.

2) Environmental sensing: These methods measure the environmental parameters, such as the concentration of carbon dioxide and humidity in the environment to estimate the total number of people in the area [10]–[12]. These methods typically require specialized hardware to be installed in an area to estimate the occupancy.

3) Device-based (active) wireless sensing: These methods estimate the occupancy in an area based on the wireless signals emitted by the devices carried by the people, such as the mobile phone [10], [13]–[15]. However, these methods may not be practical in places like retail stores and pose privacy concerns. For instance, Nordstrom, a clothing company which implemented an active WiFi-based in-store tracking technology to analyze the behavior of their customers, withdrew it due to privacy concerns of the shoppers [16]. Furthermore, the accuracy of such methods is very limited as a device can only be localized to the coverage area of the router to which it is connected in the store.

4) Device-free (passive) wireless sensing: These methods depend on the interaction of wireless signals with the people in the area of interest to estimate the total number of people

This work is funded in part by NSF CCSS award # 1611254 and in part by NSF NeTS award # 1816931

in the area [17]–[23]. Therefore, these methods do not require the people to carry any device and thus preserve the privacy of people in the area. Furthermore, as many places, such as retail stores and museums, already have wireless devices (e.g., WiFi access points) in the area, they do not require an installation of specialized hardware. **Therefore, in this paper, we focus on device-free wireless sensing for estimating occupancy in retail stores.**

All of the aforementioned passive methods on occupancy sensing focus on estimating the number of people in the area where the sensors are present. In [24], walking speed of occupants in two adjacent areas are estimated based on sensing in one area. However, only one arrival rate (or fixed number of people) is considered and assumed known.

In this paper, we are interested in estimating occupancy dynamics over a large area that consists of several sub-areas (e.g., a retail store), based on wireless transceivers that are installed in only a few areas and without relying on people to carry a device, i.e., passively. We are further interested in the general case where people can have different occupancy dynamics in different sub-areas. By estimating occupancy dynamics, we mean estimating the rate of arrival of people (the number of people per unit time) into different aisles. As the rate of arrival will be time-varying, we are thus interested in estimating it as a function of time. The existing work, however, is either not generalizable to this setting or would require a large number of wireless sensors all over the store. For instance, in a store that has hundreds of aisles, we would need to employ sensors in all the aisles in order to estimate the arrival rate of people in all the aisles.

In this paper, we propose a new method that exploits the spatial and temporal dynamics of occupancy in order to minimize the required number of sensors. More specifically, consider a scenario of a large retail store, such as a store shown in Fig. 1, with several aisles. **In this paper, we develop a new framework to estimate the rate of arrival of people into all the aisles throughout the retail store by utilizing the received power measurements of wireless transceivers in only a few aisles of the store**.[1] Thus, our framework tremendously reduces the number of required measurements, the cost associated with the hardware, and the complexity of the sensor network. To the best of our knowledge, there is no existing work (based on any kind of sensors) that can estimate the occupancy or rate of arrival in several areas, by making measurements in only a few areas. We next summarize our main contributions:

- We mathematically characterize the probability of crossing a link, for the case where people can have bi-directional flows (i.e., a person can change his/her direction at any time), and show that the rate of arrival of people into an aisle can be estimated using the received power measurements of a pair of wireless links located at each end of the aisle. The main difference of this part with the existing work [24] is considering bi-directional flows, which would require a new characterization.
- We propose a new framework to estimate the rate of arrival of people into different aisles throughout a retail store by using the received power measurements of wireless links in only a few aisles. More specifically, we exploit the sparsity in the spatial and temporal changes of the rate of arrival and propose an optimization framework to estimate the rate of arrival throughout the store. To the best of our knowledge, no existing work can achieve this. This is the main theoretical contribution of the paper.
- We implement a sensor network based on Texas Instrument CC2650 Bluetooth low energy (BLE) chips to collect RSSI measurements in a large area such as a retail store.
- We validate our framework in three different retail stores - Kmart and two other anonymous stores (Store-2 and Store-3) and show that our framework can accurately estimate the rate of arrival of people throughout the store with minimal sensing and in a device-free manner.

The rest of the paper is organized as follows. In Section II, we first mathematically characterize the probability of crossing a link and show that the rate of arrival of people, for the general case with a bi-directional flow, can be estimated using the probability of crossing the link. We then propose a framework, exploiting the spatial and temporal sparsity in the rate of arrival gradient, and formulate an optimization problem to estimate the rate of arrival of people throughout the store using measurements in only a few aisles. In Section III-A, we then propose a sensor network setup based on Texas instruments BLE chips to collect the RSSI measurements. In Section III-C, we thoroughly validate our framework with several experiments in three different retail stores, Kmart and two other anonymous stores. We conclude in Section IV.

II. Proposed Methodology and System Design

In this section, we propose a framework to first estimate the rate of arrival of people into an aisle of a retail store using two wireless links located in the aisle. We then propose a framework to estimate the rate of arrival of people into different aisles throughout the retail store based on the wireless links located in only a few aisles. We next start by summarizing the effect of people walking in the aisle on the wireless links.

A. Effect of people on the wireless links

Consider the scenario shown in Fig. 2, where people can enter/exit the aisle from either side of the aisle. A wireless link is located on each side of the aisle as shown in the figure. The wireless transmitter (Tx) transmits wireless signals that interact with the people/objects in the area and are then received by the receiver (Rx). In general, properly capturing the interaction of the people with the transmitted signal requires detailed wave modeling to capture several propagation phenomena. We have previously shown that the two main phenomena of LOS blockage and multipath suffice to capture

[1]Note that the total rate of arrival into an aisle will become the same as the total rate of departure as we shall see in the next section. Thus, we only use the term "rate of arrival" in this paper for brevity.

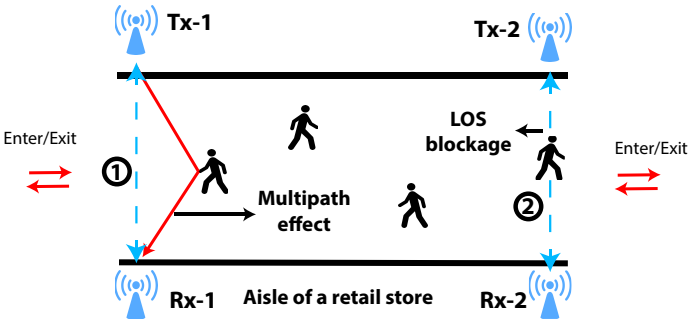

Fig. 2: A typical aisle in a retail store. People can enter and exit the aisle from either side of the aisle. Two wireless links collect received power measurements as people walk in the aisle and are located at each end of the aisle, as shown in the figure. People walking in the aisle affect the wireless links in two main ways - LOS blockage effect and multipath effect. A person blocking the LOS link significantly attenuates the RSSI signal while a person not along the LOS link reflects the signal from the Tx, resulting in random fluctuations in the RSSI measurements.

the impact of walking people on wireless transmissions. We next briefly summarize these two impacts:

1) LOS blocking: When a person is along the line joining the Tx and Rx (i.e., the LOS link), the received power measurements are significantly attenuated.

2) Multipath effect: The wireless signals from the Tx get reflected off of the people and interfere constructively/destructively at the Rx, depending on the position of the people. This causes the wireless measurements to fluctuate as people are walking. Fig. 2 illustrates the LOS blocking and multipath effects. See Fig. 5 for an experimental example of these effects.

We next propose a framework to estimate the rate of arrival of people into different aisles of a retail store, based on wireless sensing in only a few aisles. Our approach utilizes the LOS blockage effects.

B. Rate of arrival estimation in a single aisle

Consider an aisle in a retail store, a schematic of which is shown in Fig. 2. People can enter/exit from either side of the aisle, as marked in the figure. A wireless link is located at each end of the aisle and collects the corresponding received power measurements (e.g., RSSI). The objective in this section is then to estimate the total rate of arrival of the people into the aisle using the received power measurements. The main difference between the setup and characterization of this part, as compared to [1], is that [1] assumes that people entering from one side always exit from the other side. In a general retail store setting, however, people can enter from one side and exit from either sides. Thus, in this part we extend the analysis of [1] to this general setting.

Let r_1^{a} and r_2^{a} denote the rate of arrival of people and r_1^{d} and r_2^{d} denote the rate of departure of people from the sides 1 and 2 of the aisle, respectively. Let an event denote the act of any person crossing the wireless link in the aisle. Since any person entering or exiting the aisle from side 1 of the aisle causes an event on the wireless link located on side 1, the rate of events on the link at side 1 is $r_1^{\mathrm{a}} + r_1^{\mathrm{d}}$. Similarly, the rate of events on the link at side 2 of the aisle is $r_2^{\mathrm{a}} + r_2^{\mathrm{d}}$. The shoppers who enter the aisle typically spend a random amount of time in the aisle and exit the aisle from either side of the aisle. In this paper, to estimate the rate of arrival, we consider a time period larger than the typical time spent by the shoppers in the aisle. Therefore, since most people who enter the aisle also exit the aisle in this estimation time frame, we can assume that the rate of arrival into the aisle is the same as the rate of departure. We then have the following equation relating the rate of arrival and departure:

$$r_1^{\mathrm{a}} + r_2^{\mathrm{a}} \approx r_1^{\mathrm{d}} + r_2^{\mathrm{d}}. \tag{1}$$

In order to estimate the rate of arrival from the received power measurements, we next relate the rate of arrival to the probability of a person blocking (crossing)[2] a wireless link. The probability of crossing a link i, $i \in \{1, 2\}$, where i denotes the side of the aisle where the wireless link is located, is given as follows:

$$\begin{aligned} p_c^i &= \text{Number of events in time interval } \Delta \times \frac{\delta}{\Delta}, \\ &= (r_i^{\mathrm{a}} + r_i^{\mathrm{d}}) \times \delta, \end{aligned} \tag{2}$$

where $p_c^i, i \in \{1, 2\}$, is the probability of crossing the link i in the aisle, Δ is the total time period over which the rate is estimated, and δ is the time step at which the links collect the received power measurements. From equations (1) and (2), it can be easily seen that, by combining the probability of crossing of both the links, we can estimate the total rate of arrival of people into the aisle as follows:

$$r^a = r_1^a + r_2^a = \frac{p_c^1 + p_c^2}{2\delta}, \tag{3}$$

where r^a denotes the total rate of arrival of people into the aisle from both sides of the aisle. We use equation (3) to estimate the total rate of arrival in an aisle of a retail store from the probability of crossing the links located on each side of the aisle. Next, we propose a new framework to estimate the rate of arrivals of people in different aisles throughout a store by utilizing wireless links in only a few aisles.

C. Rate of arrival estimation over the whole retail store with minimal sensing

Consider a large store with several aisles, as shown in Fig. 1. Let K denote the number of aisles in the store. Let $r_i(t)$, for $i \in \{1, 2, \cdots, K\}$, denote the rate of arrival of people in the i^{th} aisle at time t, for $t > \Delta$. By rate of arrival at time t, we mean the number of people that entered the aisle in the time interval $[t, t-\Delta]$. Let $\mathbf{r}(t) = [r_1(t), r_2(t), \cdots, r_K(t)]'$ denote the corresponding rate vector, where $(.)'$ denotes the transpose of the argument. Our objective, in this section, is to estimate the rates of arrivals in K aisles by utilizing the measurements of wireless links in only a few aisles. Let M denote the number of aisles in which direct wireless measurements are made (i.e., the sensors are placed) and let $\mathbf{Y}(t)$ denote the corresponding $M \times 1$ rate of arrival vector in these M $(< K)$ aisles at time t. Fig. 3 shows a sample wireless link in an aisle. We can further obtain the summation of the arrival rates of multiple adjacent aisles by putting one

[2]Throughout this paper, we use the terms blocking and crossing interchangeably.

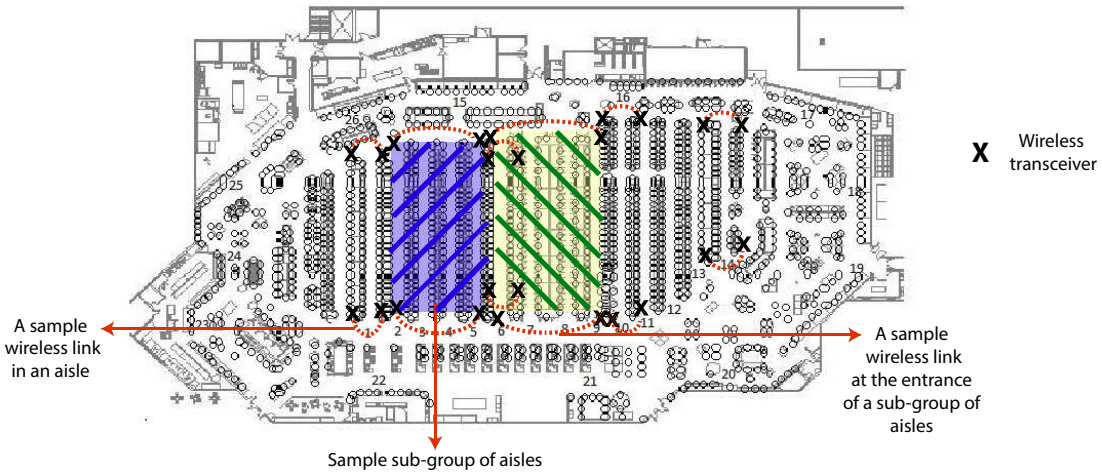

Fig. 3: The figure shows the layout of Store-3 considered in this paper. The store has 26 aisles as numbered in the figure. We consider the main group of aisles numbered from 1 to 14 for the rate of arrival estimation in section II-C. The red dashed lines indicate the wireless links. Our proposed framework of section II-C can estimate the rate of arrival of people in all the 14 aisles based only on a small number of wireless links, locations of which are indicated in the figure. Sub-groups of aisles are shown by a hashed shading.

wireless link at the entrance of multiple adjacent aisles. Fig. 3 shows a sub-group of adjacent aisles and a wireless link at each entrance of the sub-group. Let there be P such sub-regions and let $\mathbf{Z}(t)$ denote the corresponding $P \times 1$ vector of the rate of arrivals into these P sub-regions at time t. We then have the following matrix equations relating the observed rate vectors, $\mathbf{Y}(t)$ and $\mathbf{Z}(t)$, to the rate vector $\mathbf{r}(t)$.

$$\mathbf{Y}(t) = B\mathbf{r}(t) \text{ and } \mathbf{Z}(t) = C\mathbf{r}(t), \text{ for } t \in \{\Delta, 2\Delta, \cdots, N\Delta\}, \tag{4}$$

where B and C denote the observation matrices, Δ denotes the time period over which the rate is estimated, and $N\Delta$ denotes the total time period over which the measurements are made. The observation matrix B defines the aisles in which the wireless links are placed, and the rate of arrival is directly measured. More specifically, B is an $M \times K$ matrix with each row containing all zeros except at one location which has a one. This location determines the aisle in which direct measurements are made. Similarly, C is an observation matrix which determines the group of aisles for which direct measurements are made. More specifically, C is a $P \times K$ matrix with each row containing all zeros except at a few locations which has ones. These locations determine the group of aisles in which the total rate of arrival is directly measured using the wireless links.[3] In other words, we measure the sum of the rate of arrival of people into each aisle, within a group of aisles. Our objective in this section then is to estimate the rate vector, $\mathbf{r}(t)$, with the knowledge of $\mathbf{Y}(t)$ and $\mathbf{Z}(t)$.[4]

An estimate of the rate vector, $\mathbf{r}(t)$, can then be obtained by solving the following least squares problem:

$$\hat{\mathbf{r}}(t) = \underset{\mathbf{r}(t), t \in \{\Delta, 2\Delta, \cdots, N\Delta\}}{\arg\min} \sum_{t=\Delta}^{N\Delta} \Big[||\mathbf{Y}(t) - B\mathbf{r}(t)||_2^2 + \lambda_1 ||\mathbf{Z}(t) - C\mathbf{r}(t)||_2^2 \Big], \quad \text{for } t \in \{\Delta, 2\Delta, \cdots, N\Delta\}, \tag{5}$$

where $\hat{r}(t)$ denotes the estimate of the rate vector, $||.||_2$ denotes the l_2 norm of the argument, and λ_1 is a hyper-parameter. Since we measure the rate of arrivals in a relatively small number of aisles, the number of observations is relatively smaller than the number of unknowns at each time instant, i.e., $M + P << K$. As such, the optimization problem in equation (5) is ill-posed. Therefore, we next propose a method to solve this ill-posed problem based on utilizing the underlying spatial/temporal sparsity of the occupancy dynamics.

Remark: The form of the optimization problem in equation (5) is motivated by the potential difference in the accuracy of the rate of arrival measurements for a single aisle and a group of aisles. More specifically, we expect the measured rate of arrival in a single aisle to be more accurate than the measured rate of arrival in a group of aisles, as the quality of the wireless receptions degrade with the distance. Thus, we choose a weighing factor λ_1 as a model parameter to account for this potential difference.

1) Sparse spatial gradient: Consider a shopper visiting a particular aisle in a retail store. After exiting this aisle, the shopper tends to visit aisles that are close to the current aisle [25]. Therefore, we expect the number of people visiting the aisles that are adjacent to each other to be similar. More specifically, the rate of arrival vector, $\mathbf{r}(t)$, is expected to be spatially smooth. To mathematically characterize the spatial variation of the vector $\mathbf{r}(t)$ in a retail store, we model the store as a graph where each aisle is a vertex in the graph. We draw an edge between the aisles, with a weight of 1, if there is a direct path between these aisles, i.e., if a shopper can reach

[3]The procedure of making the wireless received power measurements in each aisle and the group of aisles is described in detail in section III-A.

[4]Note that we would have an estimate of $\mathbf{Y}(t)$ and $\mathbf{Z}(t)$ using the method of section II-B.

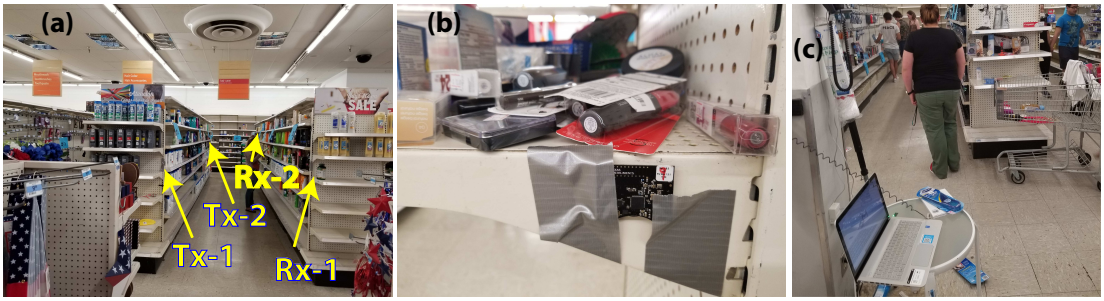

Fig. 4: (a) The figure shows the considered aisle in the retail store Kmart. Our objective in this store is to estimate the rate of arrival of people into this aisle. Four wireless transceivers (TI CC2650 BLE chips) are located on each corner of the aisle, as marked. Two of the nodes are used as Tx's and the other two as Rx's. The Tx and Rx on each side of the aisle form a wireless link and collect the BLE RSSI measurements. (b) TI CC2650 BLE chip used for collecting the RSSI measurements in the store. (c) A laptop, with CC2531 BLE dongle attached to it, collects and stores the RSSI measurements from the two wireless links in the aisle.

from one aisle to the other without going through any other aisles. Let L denote the Laplacian of the resulting graph as defined below.

$$L = D - A, \tag{6}$$

where A denotes the adjacency matrix of the graph, and D is a diagonal matrix with each diagonal entry representing the degree of the corresponding vertex. The following quantity then represents the spatial variation of the rate of arrival of people in different aisles of the store:

$$\mathbf{r}(t)' L \mathbf{r}(t) = \frac{1}{2} \sum_{i \neq j} w^{i,j} (\mathbf{r}_i(t) - \mathbf{r}_j(t))^2, \tag{7}$$

where $w^{i,j}$ denotes the weight of the edge between the vertex i and vertex j, $\mathbf{r}_i(t)$ and $\mathbf{r}_j(t)$ denote the i^{th} and j^{th} entry of $\mathbf{r}(t)$, respectively, and $(.)'$ denotes the transpose of the argument. Thus, minimizing the quantity in equation (7) promotes the spatial smoothness of the rate of arrival in different aisles of the store.

2) Sparse temporal gradient: The overall rate of arrival of people into a retail store, on a given day, changes slowly with the time of the day as observed in multiple retail stores [26]. Since the rate of arrival of people into each aisle of the store is proportional to the total rate of arrival into the store, we expect the rate of arrival vector to also have sparse variations with time. Thus, we regularize the optimization problem (5) by adding the l_1 norm of the time variations in the rate vector, $||\mathbf{r}(t) - \mathbf{r}(t-1)||_1$, to promote the sparsity in time variations.

By incorporating the spatial and temporal variation terms of the rate of arrival in the optimization problem (5), we then get the following regularized problem:

$$\hat{\mathbf{r}}(t) = \underset{\mathbf{r}(t), t \in \{\Delta, 2\Delta, \cdots, N\Delta\}}{\arg\min} \sum_{t=\Delta}^{N\Delta} \Big[||\mathbf{Y}(t) - B\mathbf{r}(t)||_2^2 + \lambda_1 ||\mathbf{Z}(t) - C\mathbf{r}(t)||_2^2 + \lambda_2 \mathbf{r}(t)' L \mathbf{r}(t) + \lambda_3 ||\mathbf{r}(t) - \mathbf{r}(t-1)||_1 \Big] \quad \text{for } t \in \{\Delta, 2\Delta, \cdots, N\Delta\}, \tag{8}$$

The optimization problem (8) is convex in $\mathbf{r}(t)$. Therefore, we use the CVX solver [27] to solve (8) and estimate the rate of arrival of people in different aisles of the store as a function of time. We next validate our framework with several experiments.

III. Performance Evaluation

In this section, we validate our framework with several experiments in 3 different retail stores. We first describe our experimental setup to collect the RSSI measurements in the retail stores. We then first show several results obtained in the retail stores Kmart and an anonymous retail store (Store-2 in our town). In these two stores, we physically insert wireless links in one aisle and show how we can robustly estimate the arrival rate of the shoppers in the corresponding aisle. We also identify interesting trends in the occupancy dynamics. In order to validate our framework over the whole store, we then use a large online dataset from an anonymous retail store (Store-3), and robustly estimate the rate of arrival of people into different aisles throughout the store, based on measurements in only a few aisles, thus significantly reducing the number of required sensors and the complexity of the system.

A. Experiment setup

In this paper, we use Texas Instrument TI CC2650 system on chips to collect the RSSI measurements as people walk in the store [28]. Fig. 4 illustrates the experimental setup. TI CC2650 is a system on chip that contains ARM cortex microprocessor and an RF core targeted for BLE and Zigbee applications. It is designed to operate on a coin cell battery for more than a year and is hence suitable for applications which require minimal manual interference. We use the CC2650 chips with RF core configured to BLE protocol. To estimate the rate of arrival of people into an aisle, we utilize two BLE links placed on each side of the aisle, as shown in Fig. 4(a). Each link uses two TI CC2650 chips, one configured as a Tx and the other as an Rx. As per the BLE specification, each device can be in one of the following modes - broadcaster, observer, peripheral, and central. In the broadcast mode, a device simply transmits BLE beacons without any requirements for acknowledgments. In the observer mode, the device scans for any BLE beacons in the area. The devices need to be in peripheral or central modes when they need to establish a connection with another device for the purpose of data transfer. Since, in this paper, we only need to measure the RSSI of each link, we utilize only broadcast and observer roles for the BLE devices. More

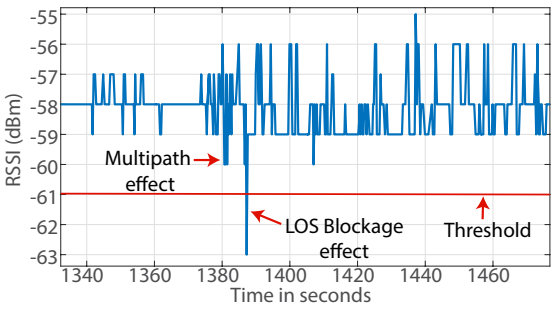

Fig. 5: A sample wireless measurement. The effects of people walking in the aisle on the RSSI measurements are marked: The LOS blockage effect results in strong attenuations while the multipath results in random fluctuations in the RSSI measurements. We threshold the RSSI measurements to separate the LOS blockage effect from the multipath effect, as shown in the figure.

specifically, we configure the Tx chip to broadcast Bluetooth beacons at regular intervals of time. The Rx is configured to the observer mode where it keeps scanning for the BLE beacons. Since there could be other BLE devices in the area that are broadcasting, the receiver is configured to listen to beacons only from the corresponding Tx. The receiver is also configured to measure the RSSI when it observes the BLE beacon from the corresponding Tx of the link. Since the memory on the chip is limited, we switch the receiver from observer mode to the broadcast mode, after measuring the RSSI value, in order to broadcast the measured RSSI value. The receiver is then switched back to the observer role to measure the next RSSI value. A laptop then listens to all such broadcasts from the receivers and stores the RSSI measurements of all the links in the area. More specifically, we run the TI packet sniffer program to capture all the BLE packets and store the BLE packets from the receivers of all the links. Since off-the-shelf laptops are not equipped with BLE radios, we use a TI CC2531 BLE dongle (connected to a laptop) to receive the Bluetooth packets, as shown in Fig. 4(c). To capture the dips in the RSSI values, associated with a person crossing the link,[5] we configure the transmitter and receiver of each link to measure the RSSI values at a rate of 20 times/sec. Furthermore, the Tx and Rx are set to transmit BLE beacons at 0 dBm power.

B. Separation of LOS from MP

In section II, we discussed that people walking near the BLE link can affect the RSSI measurements through LOS blocking and multipath effects. In section II, we proposed a framework to estimate the rate of arrival of people into different aisles based on LOS blockage effect. Therefore, in this section, we briefly summarize how we can extract the LOS blockage events from the RSSI measurements.

We have previously shown that the fluctuations in the RSSI measurements due to multipath are concentrated around the mean level of the RSSI signal, while blocking the LOS causes a more pronounced dip in the signal level [19]. Therefore, following the same procedure as in our past work, we contribute any dip in the RSSI signal level that is larger than a sufficiently-large threshold to people blocking the LOS link. Fig. 5 illustrates a dip due to LOS blockage, fluctuations due to multipath, and the threshold.

C. Experimental results and discussion

In this section, we experimentally validate our framework using several experiments in three different retail stores, using the aforementioned experimental setup. We start by validating that we can robustly estimate the rate of arrival in the aisles where the wireless links are. We then show how we can estimate the occupancy attributes in several other aisles, based on wireless sensing in only a few aisles.

1) Occupancy estimation in the sensed aisles: Kmart and Store-2: We obtained permission from our local Kmart store as well as another large retail store that shall remain anonymous[6] (referred to as Store-2 here) to put wireless links in one aisle in each store. In this part, we extensively discuss our findings along this line.

We start by considering the setup in Kmart. Fig. 4(a) shows the aisle where we put two wireless links, based on the experimental setup described in the previous section. The ground-truth rate of arrival of people in the aisle is obtained by manually counting the number of people in the security camera footage covering the aisle. Fig. 6 and 7 show the estimated and true rate of arrival in the aisle on two different days (Monday and Friday) and for 1 hour respectively, using our framework. Here, the rate of arrival is measured as the number of people per each 10 minute time interval. It can be seen that our framework accurately estimates the rate of arrival and its trends. For instance, the average error in the rate of arrival estimation is 0.15 people/min on day-1 (Monday), when the true average rate of arrival is 0.44 people/min, and 0.2 on day-2 (Friday) when the true average rate of arrival is 0.85. Thus the error is very small as compared to the true rate of arrival, which confirms the accuracy of our framework.

Weekday vs Weekend: Fig. 6 and 7 showed the true and estimated traffic on Monday and Friday respectively. By plotting them on the same graph, we can see interesting underling trends for the traffic as a function of the day. More specifically, Fig. 8 shows the estimated and true arrival rate for both of these days. In general, it is expected that the traffic in the store is higher during the weekend time, which is captured by the true and estimated rate of arrival in Fig. 8. Such analysis can help the retail stores obtain valuable occupancy analytic, without relying on cameras (thus preserving the privacy), and plan their resources accordingly.

We next discuss the experimental results obtained in Store-2. Fig. 9 shows the estimated and true rate of arrival in the aisle where we installed the wireless links, for a period of 1 hour. It can be seen that the estimated rate closely follows the true rate. For instance, the average error in the rate of arrival is 0.18 people/minute when the true average rate of arrival of

[5]In this paper, we do not consider the case of multiple people simultaneously crossing a link, as it is a low probability event in an aisle-type scenario.

[6]The name of the store is withheld for the anonymity per request of the store.

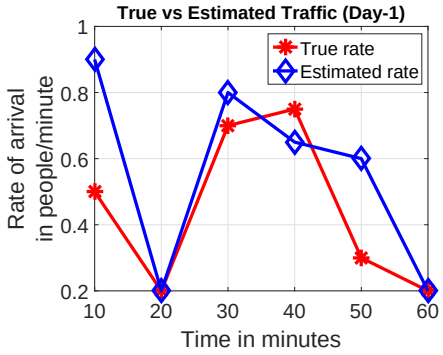

Fig. 6: The figure shows the true and estimated rate of arrival of people, using our framework, in an aisle in Kmart on day-1. It can be seen that the estimated rate closely matches the true rate.

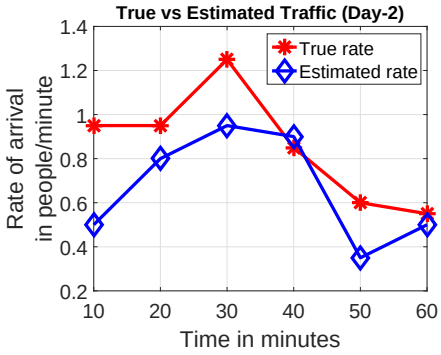

Fig. 7: The figure shows the true and estimated rate of arrival of people, using our framework, in an aisle of Kmart on day-2. It can be seen that the estimated rate closely matches the true rate.

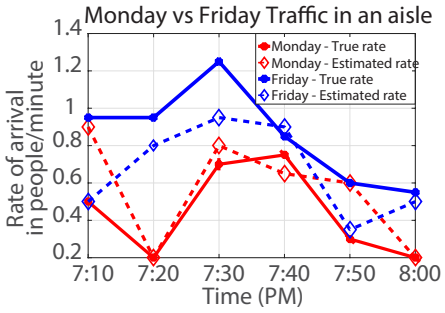

Fig. 8: The figure shows the true and estimated rate of arrival of people in the aisle of the Kmart store on both Monday and Friday. It can be seen that the traffic on Friday is higher than on Monday, which is correctly estimated by our framework.

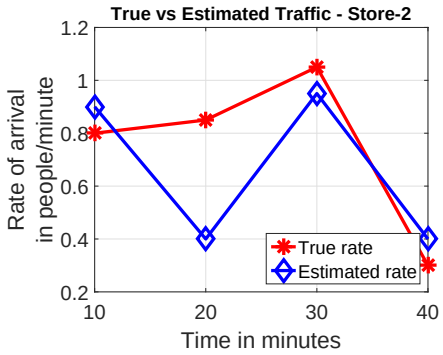

Fig. 9: The figure shows the true and estimated rate of arrival of people, using our framework, in the aisle of Store-2. It can be seen that the estimated rate closely matches the true rate.

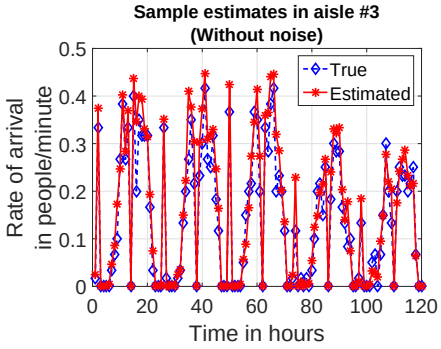

Fig. 10: The true and estimated rate of arrival of people in Aisle-3 of Store-3, obtained using our framework. It can be seen that the estimated rate closely matches the true rate.

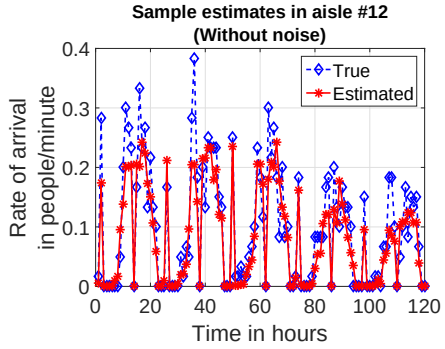

Fig. 11: The true and estimated rate of arrival of people in Aisle-12 of Store-3, obtained using our framework. It can be seen that the estimated rate closely matches the true rate.

people in the considered aisle is 0.75 people/minute, which further establishes the robust nature of our framework.

2) Occupancy estimation over the whole store (Store-3): So far, we have presented the experimental results for estimating the rate of arrival in the aisles where the wireless links are present. In this section, we validate our framework to estimate the rate of arrival in different aisles of a store based on wireless links located in only a few aisles. For this purpose, we utilize an online dataset from a large anonymous retail store [29].[7] The dataset contains the trip details of each shopper. More specifically, the data contains the location of the shopper in the store at each time instant, while the shopper is walking in the store. Thus, we can evaluate the number of people visiting each aisle in a given time period, i.e., the rate of arrival of people into each aisle. We then use this online dataset to validate the proposed framework of section II-C.

Fig. 3 shows the floor plan of Store-3. This store contains 26 different regions, as labeled in the figure. The regions 1 to 14 are the main aisles in the store whereas the regions labeled 15 to 26 are the regions in the corners and the edges of the store. In this section, we validate our framework using the occupancy data in aisles 1 through 14. More specifically, we utilize the knowledge of the rate of arrival of people in the aisles 1, 6, 10, and 14 and the knowledge of the total rate of arrival of people into two groups of aisles, $2-5$ and $6-9$, and the knowledge of the total rate of arrival of to estimate the rate of arrival of people in all the aisles, i.e., aisles 1 to 14. The knowledge of the rate of arrival of people in individual aisles can be obtained by placing wireless links in these aisles, as we throughly verified in Kmart and in Store-2. Similarly, the rate of arrival of people into a sub-group of aisles can be obtained by considering the sub-group of aisles as one big aisle and placing the wireless links accordingly. For instance, to estimate the rate of arrival in the sub-group of aisles $2-5$, we insert the Tx-1 and Tx-2 of the two wireless links on each end of aisle-2 and the Rx-1 and Rx-2 of the two wireless links on the corresponding ends of aisle-5. Fig. 3 shows the locations where the wireless links would be, for sensing in the individual aisles as well as for sensing in the 2 sub-group of aisles. Without the proposed framework of this paper, we would have to put sensors in all the aisles, which would require 56 nodes (2 nodes for each wireless link). By using our framework, on the other hand, we sense the rate of arrival in only 4 aisles and two groups of aisles, thus requiring only 24 sensor nodes. Therefore, we achieve a 57% reduction in the number of required sensor nodes. Since the data for this store is only available online, we cannot manually put wireless links for

[7]We note that we did not have permission to visually monitor the security footage covering all the aisles in the aforementioned local Kmart and Store-2 to build the ground truth for this part. As such, we are using the large available online dataset for Store-3.

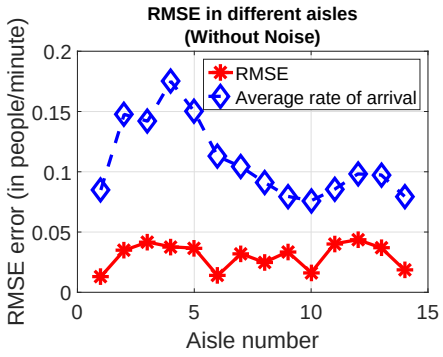

Fig. 12: The average RMSE in estimating the rate of arrival of people in each aisle of Store-3. It can be seen that the RMSE error is very small compared to the true average rate of arrival of people.

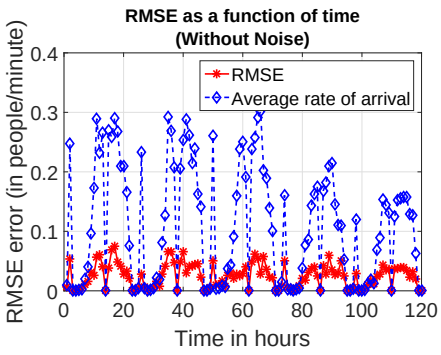

Fig. 13: The average RMSE in estimating the rate of arrival of people, averaged across all the aisles in Store-3, as a function of time. It can be seen that the RMSE error is very small compared to the true average rate of arrival of people.

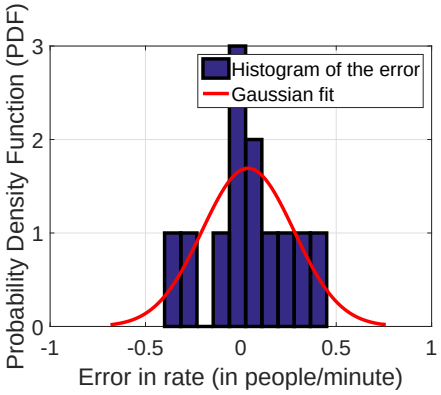

Fig. 14: The figure shows a histogram of the error in the rate of arrival estimation in the Kmart store. A Gaussian fit to the error is also shown. This Gaussian noise is used to validate the robustness of our framework.

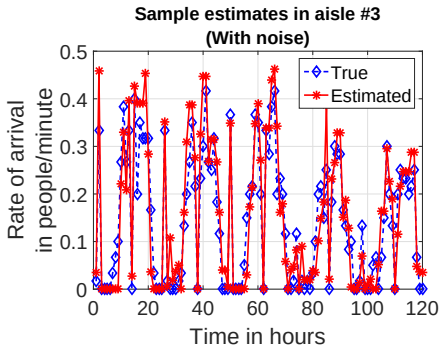

Fig. 15: The true and estimated rate of arrival of people in Aisle-3 of Store-3, obtained using our framework, in the presence of noise. It can be seen that the estimated rate closely matches the true rate.

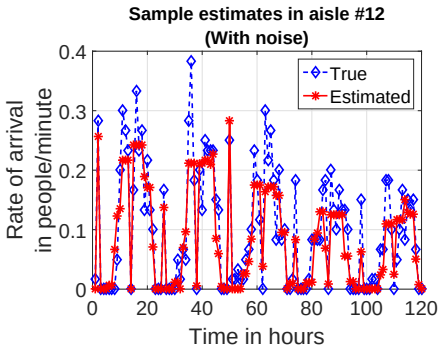

Fig. 16: The true and estimated rate of arrival of people in Aisle-12 of Store-3, obtained using our framework, in the presence of noise. It can be seen that the estimated rate closely matches the true rate.

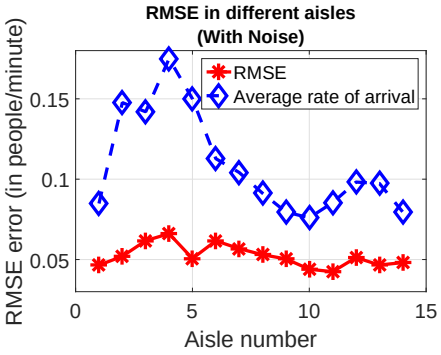

Fig. 17: The average RMSE in estimating the rate of arrival of people in each aisle of Store-3. It can be seen that the RMSE error is very small compared to the true average rate of arrival of people, even in the presence of noise.

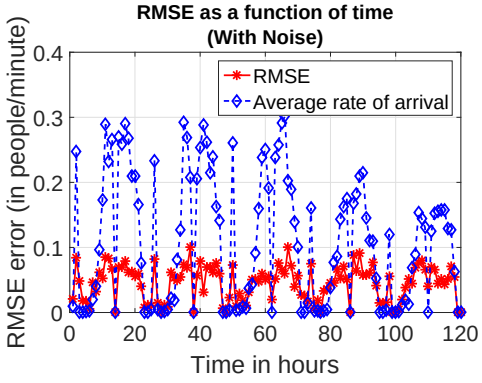

Fig. 18: The average RMSE in estimating the rate of arrival of people, averaged across all the aisles in Store-3, as a function of time. It can be seen that the RMSE error is very small compared to the true average rate of arrival of people even in the presence of noise.

direct sensing in the aforementioned aisles/sub-groups. Thus, we first test our proposed sparsity-based framework by using the true arrival rate in the sensed aisles. We then add noise (with the proper statistics) to the true arrival rate of the sensed aisles/sub-group, and show the performance of our approach. We next show the performance of our framework in this store.

Fig. 10 and 11 show the sample estimated rate of arrival in Aisle-3 and Aisle-12 of the store, respectively, for a period of 120 hours. It can be seen that the estimated rate of arrival is very close to the true arrival rate in these aisles. To characterize the performance of our framework over all the aisles 1-14, we next look at the average root mean square error (RMSE), averaged across different time periods and different aisles.

Fig. 12 shows the average RMSE in the rate of arrival estimates in each aisle, averaged over 120 hours. The figure also shows the average true rate of arrival in each aisle, averaged over the 120 hour time period. It can be seen that the RMSE error is very small as compared to the true rate of arrival in all the aisles. Fig. 13 shows the average RMSE error in the rate of arrival estimation at each time, averaged over all the aisles. It can be seen that the RMSE error is very small as compared to the true rate of arrival at each time. Overall, the error in rate of arrival estimation, averaged over all the aisles and over 120 hour time period, is 0.03 people/minute when the true average rate of arrival is 0.11 people/minute, thus showing the accuracy of our framework.

So far, we validated our sparsity-based framework for Store-3 when the true rate of arrival in sensed aisles/sub-groups is known. However, when the rate of arrival is estimated by actually placing the wireless links in the aisles, we can only

get an estimate of the true rate of arrival, as we showed in section III-C1. Therefore, we next validate our sparsity-based framework in the presence of errors in the rate of arrival estimation for Store-3. Since Store-3 data is only available online, we first characterize the noise in the rate of arrival estimation, by utilizing the data collected in the aisle of the Kmart store. More specifically, we use the 2 hours of the data we collected in the aisle of the Kmart store and estimate the probability density function (PDF) of the error in the rate of arrival estimation. Fig. 14 shows this PDF. Since the error PDF resembles the Gaussian density function, we fit a Gaussian PDF to the error PDF and estimate the corresponding parameters of the Gaussian PDF. We then add a Gaussian noise with the estimated parameters to the true rate of arrivals of the online data set of Store-3. Thus, this process simulates the effect of collecting the data by physically placing the wireless links in the aisles. We next show the performance of our framework for this scenario, for the same case of direct sensing for aisles 1-14 and sub-groups $2-5$ and $6-9$.

Fig. 15 and 16 show the estimated and the true arrival rates in Aisle-3 and Aisle-12, respectively. It can be seen that the estimated rate is close to the true rate of arrival, even in the presence of noise. Fig. 17 and 18 show the average RMSE errors as a function of the aisles and time. It can be seen that the average RMSE error is very small as compared to the true rate of arrival. Thus our framework can robustly estimate the rate of arrival throughout the store with minimal sensing.

IV. Conclusions

In this paper, we proposed a new framework to estimate the rate of arrival of people over the aisles of a large retail store, based only on the received power measurements of wireless links that are located in only a few aisles, and without relying on people to carry any device. We first showed how to estimate the rate of arrival of people into an aisle, for the case where people have a bi-directional flow, based on the received power measurements of two wireless links that are located in the aisle. We then exploited the spatial and temporal smoothness of the occupancy dynamics over the whole store and formulated an optimization problem to estimate the rate of arrival throughout the store, based only on a small number of wireless links that are installed in a few aisles. To validate our proposed framework, we developed an experimental setup, using TI CC2650 BLE chips, and ran experiments in three different retail stores - Kmart, two other anonymous stores, and showed that our approach can estimate the rate of arrival of people in different aisles of a store with minimal sensing (57% reduction in the number of required wireless links) and with a high accuracy (average root mean square of 0.03 people/minute when averaged over all the aisles and time).

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