Role of Campus WiFi Infrastructure for Occupancy Monitoring in a Large University

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***Abstract*—Wireless infrastructure such as WiFi access points (APs) has grown in popularity while we witness an increased use of wireless smart devices among communities worldwide. Therefore it is desirable to use metadata from the WiFi APs for sensing occupancy as opposed to dedicated physical sensors. In this paper, we (a) compare the performance of WiFi-based occupancy sensing with hardware-based occupancy sensing at room level and then analyze hourly WiFi data across the UNSW campus (b) to understand the applications of occupancy monitoring using WiFi data in a campus environment. Our study explains the feasibility of using WiFi metadata for room-level occupancy estimation by comparing the performance with hardware beam counter sensors while adding insights on how campus communities can benefit from using lightweight WiFi infrastructure for occupancy sensing.**

***Index Terms*—WiFi, occupancy monitoring, university campus**

I. Introduction

The wireless infrastructure is ubiquitous in modern day universities, offering daily internet to the entire campus community. University campuses comprise of a variety of different spaces including teaching, learning, office, residential and retail buildings. Having visibility into the real-time occupancy of different spaces is beneficial to a number of applications, ranging from Heating, Ventilation, and Air Conditioning (HVAC) of buildings, optimal resource allocation, security surveillance to network load balancing. A reliable, scalable and sufficiently accurate occupancy monitoring is the underlying necessity for any such application.

On the other hand, there are different types of stakeholders in a university campus whose demands are very different to each other. The campus estate management aims to optimize resource allocation while increasing their revenues. The major portion of the campus community are students who aim to access campus facilities while saving their time and money. Thirdly, there are on-campus retailers who provide third party facilities such as restaurants, bookshops, travel related services and banking and they aim to enhancing their revenues at minimal cost. Currently, the vast majority of the stakeholder decision making is based on anecdotal data, hence would not scale properly to provide realistic information on occupancy. While a large network of dedicated occupancy sensors is the most ideal way of occupancy monitoring, associated expenses of deployment at campus-scale can be prohibitively high. To this end the, existing wireless infrastructure can act as soft occupancy sensors, especially in a large university campus.

In this paper, we first compare the performance of WiFi sensed room occupancy with that of the room occupancy sensed by hardware beam counter sensors. By collecting beam counter sensor and WiFi AP data from 4 classrooms on UNSW campus we discuss the effectiveness of using WiFi AP data to monitor occupancy in a campus environment. Secondly, we discuss why we are in favor of WiFi as a soft sensor in occupancy monitoring by analyzing the WiFi AP data collected during 4 week period across the whole UNSW campus. Furthermore, we explain how different campus stakeholders can benefit from occupancy information based from realistic data collected across the whole campus.

The paper is organized as follows: In Section II we discuss the prior work while the Section III presents our case study of comparing beam counter sensed occupancy, $Occupancy_{BC}$, with WiFi sensed occupancy, $Occupancy_{WiFi}$. Then we add insights to the data collected from all the WiFi APs across our campus and discuss the broader applications of WiFi sensed occupancy in a campus environment in Section IV. Finally we conclude the paper in Section V.

II. Related Work

In the current literature, occupancy monitoring has been mostly based on data collected from sensors specifically installed for the purpose. However with WiFi networks being readily available in many commercial complexes such as hospitals, companies and university campuses, using WiFi APs as occupancy sensors have become popular. In this section we focus on the prior work of occupancy monitoring based on existing WiFi infrastructure.

Occupancy estimation in building level was studied by Melfi et. al [1] and Balaji et. al [2], however the focus was more on analyzing the ability to use WiFi network accurately to count number of people in a room. Ouf. et. al. [3] has compared the WiFi sensed occupancy with the occupancy deduced by CO2 sensors. They have shown that the WiFi sensed occupancy correlated to actual occupancy with a correlation coefficient of 0.839 while that shown by CO2 concentration levels was 0.728.

The study by Sevtsk et. al [4] was the first to analyze WiFi log files on a campus where they aimed to understand the daily working and living patterns of campus community of Massachusetts Institute of Technology (MIT). They collected WiFi log files from MIT campus, mapped the WiFi usage to occupancy and identified daily peaks of WiFi usages and how WiFi activity indicated predictive patterns in different venues such as academic and residential buildings. They have highlighted that WiFi occupancy can be used as a crude approximation for occupancy. However with the proliferation of Internet of Things (IoT), smart devices and WiFi infrastructure are more common than the time that their study was carried. Ruiz-Ruiz et al. [5] have suggested analysis methods to extract information from a large WiFi network where they perform a case study of a hospital test bed. They extracted a set of spatial and temporal features from WiFi data to determine presence, movement and user roles in a hospital, however the focus was to introduce new methods of analyzing data. Alessandrini et. al [6] monitored flow of people by setting up an AP network during an Open Day event and showed that the people flow was compatible with the scheduling and the progression of the event. They have collected official data record for the event to compare such data with the spatial and temporal WiFi occupancy during the event. However, in a university campus such comparison is not feasible as universities do not hold track of people entering and exiting the campus with the associated events.

Our work is different from the WiFi sensor based occupancy monitoring in prior work as we start from comparing room level WiFi occupancy with beam counter sensed occupancy and then give insights on a set of applications based on occupancy monitoring in a campus environment. To the best of our knowledge, this work is the first to investigate WiFi AP data and beam counter sensor data simultaneously to detect room occupancy and discusses the effectiveness of using WiFi in a large university campus.

III. Approaches to Classroom occupancy monitoring

There are various approaches of monitoring room occupancy ranging from using sensing devices such as break beam sensors and passive infrared (IR) sensors, camera-based methods by performing image and video analytics, to utilizing existing infrastructure such as WiFi APs. Each of these methods has its own pros and cons in terms of cost, installation requirements, privacy, and accuracy. In this section, we compare two methods, the first being sensor-based approach using beam counter sensors installed at every doorway to capture the number of people entering and exiting a room and the other method involves using metadata from existing WiFi APs to estimate classroom occupancy.

A. Data Collection

To compare the two approaches, we use the data collected from beam counter sensors and WiFi APs for 4 various sized classrooms during a semester. In this section, we explain how the two methods are used to derive the number of occupants in a room.

1) Beam Counter Data Collection: The beam counter consists of a pair of sensors which are positioned across a doorway, each generates an IR beam. They are used to count the number of people passing through the beam in each direction. Beam counters are installed at every doorway of the room (e.g. BC1 - BC4 in Fig. 1 for classroom CLB), ensuring all entries and exits of the room are captured. The data generated from these sensors are collected every 30 seconds, and stored into a database.

2) WiFi Data Collection: We collected the WiFi metadata such as number of connected users (i.e. a unique user id and password is required for authentication in enterprise network) and devices (i.e. MAC address) related to each of the connections made at the APs located in rooms to compute classroom occupancy. The APs located in classroom CLB8 (AP1 to AP9) are shown in Fig. 1.

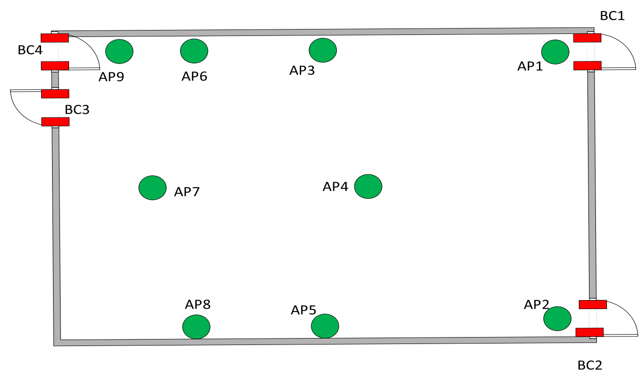


Fig. 1: Room layout with doorways, beam counters, and APs in lecture hall CLB8.

B. Data Analysis

We computed classroom occupancy from the data generated from beam counters by summing the total entries and exits across all doorways of a classroom. The WiFi signals are not contained within the rooms, hence transient users who passerby are also counted. Therefore we first filter sessions those which lasted less than five minutes. Then the occupancy from WiFi data is derived by summing the number of unique users connected across all APs inside the room.

In Fig. 2, we compare the computed occupancy of classroom CLB8 obtained from beam counters (green line) and WiFi metadata (blue line) for each day of a week during the period between 31-Jul-2017 to 06-Aug-2017. We overlaid enrollment number (red line) to the plot during the time when classes are scheduled. The plot provides an overview comparison between the two approaches which yielded a similar occupancy measurements and are closely related to the class timetable. For example by looking at the occupancy calculated on Monday, we observe that 5 classes, each with 1-hour duration, are scheduled back-to-back from 9am to 2pm, followed by a 2 hour class (2pm-4pm), and finally a 3-hour class from 5pm to 8pm.

For this sample room CLB8, we observe a consistent occupancy pattern in both approaches (i.e. the beam counter

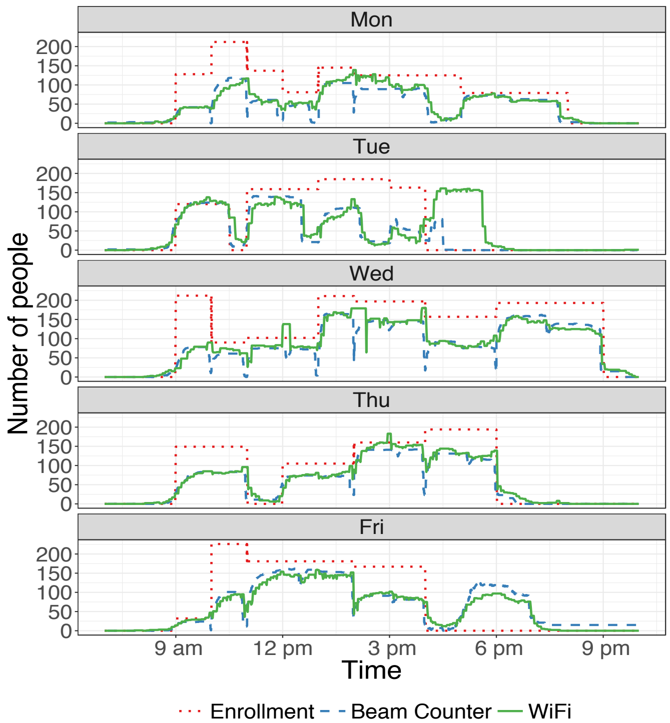


Fig. 2: Comparison of two methods for CLB8 across a week.

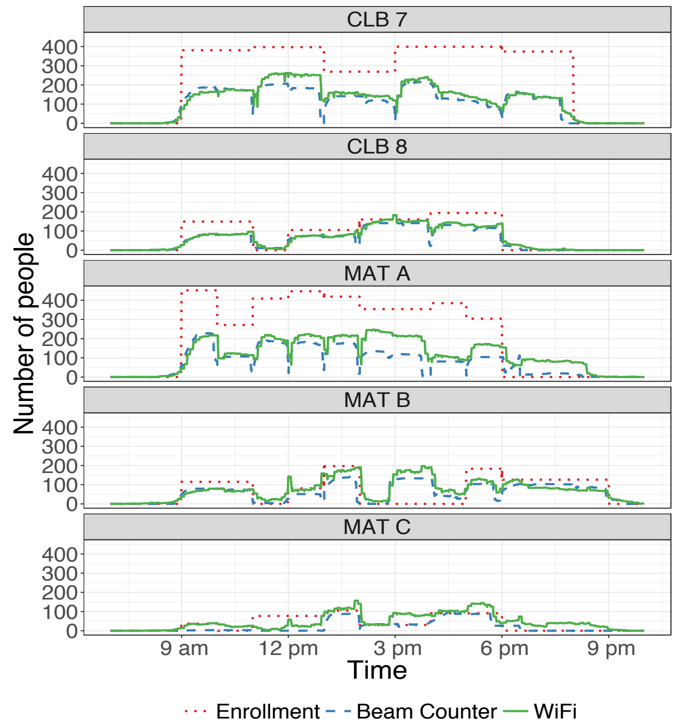


Fig. 3: Measurement variation of two methods across rooms.

and the WiFi metadata) across a week. But, this varies across different rooms where classroom size and layout change. Fig. 3 shows the variation of occupancy pattern obtained from the two methods for 5 different rooms for a single day. The occupancy pattern for room CLB8 seems to be similar for both sensing methods whereas $Occupancy_{WiFi}$ seems to be higher than $Occupancy_{BC}$ in the other rooms, because lecture rooms such as MATA and MATB have wider doorways where beam counters are unable to capture individuals who are walking side-by-side.

C. Comparison of approaches

Accuracy: To evaluate the accuracy of the beam counter and WiFi metadata in measuring classroom occupancy, we collected 37 samples of actual occupancy from 4 classrooms. Fig. 4 shows how the occupancy obtained from sensed data relates to the observed occupancy. The Pearson's product-moment correlation for the two cases was computed and the correlation coefficient (R) between the WiFi sensed and the observed room occupancy indicated a strong statistical significance with a R of 0.85 while a relatively weak relationship was found between the beam counter sensed and the observed occupancy with a R of 0.68. Furthermore, we computed the overall symmetric mean absolute percentage error (SMAPE) (1) and the SMAPE for different classrooms as shown in Table I.

$$sMAPE = \frac{100\%}{n} \sum_{i=1}^{n} \frac{| F_i - A_i |}{| F_i | + | A_i |} \quad (1)$$

where A_i is the actual value, F_i is the predicted value for ith input of n inputs.

The overall SMAPE was 12.1% for $Occupancy_{WiFi}$ and 15.6% for $Occupancy_{BC}$. The results verify our hypothesis that WiFi based occupancy sensing is comparable to dedicated hardware sensing and in this case over-performed beam counter sensing in counting number of people at room level. However, we should also note that in our comparison the error was biased to the fact that 30 out of 37 observed occupancy are from large lecture theaters with wide doorways where there is a bottleneck in beam counters as they may not capture individuals walking side-by-side.

The higher correlation between the actual occupancy and the WiFi occupancy suggested that WiFi sensed occupancy can be used as a close approximation to the actual occupancy on the campus environment even at higher spatial resolutions such as rooms. The SMAPE calculated for different rooms found to be nearly similar which gives evidence that our results are generalizable across the campus.

TABLE I: Comparison of SMAPE for different rooms.

	room capacity	beam counter	WiFi
MAT A	472	20.9%	9.6%
MAT B	246	10.0%	15.1%
CLB 7	497	20.4%	9.9%
CLB 8	231	11.6%	13.3%

Cost: Since WiFi metadata is collected from readily available WiFi APs, we consider there is no financial costs associated with this method in acquiring occupancy measurements. On the other hand, there is a cost associated with every pur-

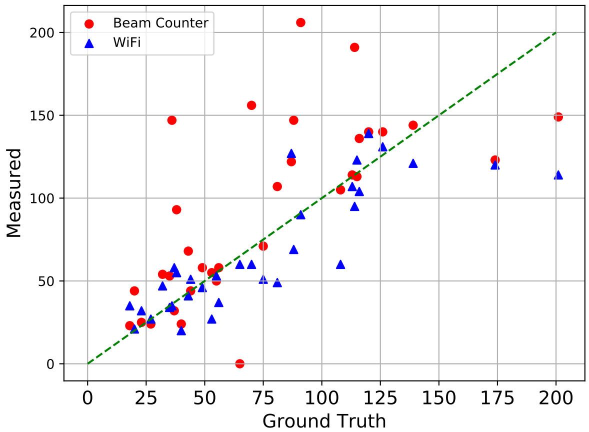


Fig. 4: Measured occupancy versus ground-truth occupancy

chase of a beam counter device which is directly proportional to the number of classrooms we aim to equip. Hence, WiFi based method is more preferable where cost is an important factor for the implementation.

Installation: There are no installation requirements involved in using WiFi APs as the data is readily available from the existing network infrastructure of the university campus. Once a system is set up to collect data no intervention is needed. Beam counter, however, requires human labor to install each sensor across the doorways. As beam counters need to communicate to a gateway that has to be connected to our private VLAN via Ethernet and it is needed to provision network ports to enable data communication.

Intrusiveness: Both the methods, beam counter and WiFi AP based, collect the data passively without requiring users to perform any extra action. Thus both methods are considered to be non-intrusive.

Privacy: WiFi metadata contains user identifiers with which the university community get connected to the wireless network, hence can endanger students privacy. The beam counters, on a contrary, is privacy preserving since it only sense the number of people entering or exiting the room without collecting any private data of the individuals.

D. *Discussion*

Although metadata from WiFi connection logs provide similar performance as the physical sensors and do not incur additional costs as opposed to physical sensors, there are some shortcomings. Most importantly, WiFi logs (based on the experience from our own campus network) are only available once every one hour whereas data from beam counters is available in real-time (i.e. at least twice a minute). Another issue is the computational complexity. For the specific classroom we have studied, we obtain counts in and out every 30 seconds, meaning a total of 960 data points per hour as beam counter sensor data from the 4 doorways, hence the computational cost is relatively small compared to that of hourly WiFi connection logs. From the 9 WiFi APs in the particular classroom, we receive data matrix of 100 to 1000 rows (depending on the number of enrollment for scheduled classes) and 14 columns on average – this is much heavier compared to beam counter data. Yet, beam counters can only be used for closed spaces with doorways, thus WiFi metadata seems a more scalable option for occupancy monitoring in a large university campus. The associated costs in installation and maintenance in beam counters when combined with the fact that they can only be used for closed spaces with a given structure (e.g. with doorways) limits beam counters to be used across the campus for occupancy monitoring while WiFi is an already available infrastructure where we only need to set up a system to harvest data.

Therefore, we propose that WiFi metadata should be used at campus-wide occupancy monitoring to get visibility of all the spaces whereas for particular spaces of which we are interested in obtaining real time occupancy beam counters are the most ideal.

IV. Broader Applications of WiFi Data

To analyze building level and campus level occupancy, we have collected 4-weeks of WiFi data from 9-Jul-2018 to 6-Aug-2018 for all APs across the campus. For this purpose, UNSW IT department maintains an Application Programming interfaces (API) which can produce number of connected devices in real time. For each AP, the number of devices connected was recorded on an hourly basis. However, number of devices can be different from number of people because of the over-count due to single users having multiple connections and people not having connected to WiFi. We can map the device count to people count by computing a proportionality factor of average devices per user. Based on our experiment in July 2018, we found that each student on average has 1.3 devices conencted to the campus WiFi – this number can vary over time and may depend on specific location of the campus but is indeed helpful in mapping the connected device to the actual occupancy. We assume the fraction of people without WiFi connection is small, therefore can be ignored.

A. *Occupancy on campus*

The UNSW wireless AP network consists of nearly 5000 APs. In Fig. 5 we have shown the total number of connected devices across all the APs on the campus during 09-Jul-2018 to 05-Aug-2018. From left to right on the figure, we notice that the number of WiFi connections rise from 20,000 - 30,000 in first 2 weeks to 50,000 - 70,000 connections in the next 2 weeks during weekdays. We intentionally started collecting data two weeks prior to commencement of a new semester and continued for two weeks after that – the vertical dashed red line separates the two periods in Fig. 5. Therefore we see a significant increase in WiFi connections during the week days as the semester starts. However, the number of WiFi connections made during the weekends increases only by 10,000 connections. This increase is probably because students are back to on-campus accommodation. The baseline for WiFi connections made during the weekend regardless of university vacation can be estimated to nearly 10,000.

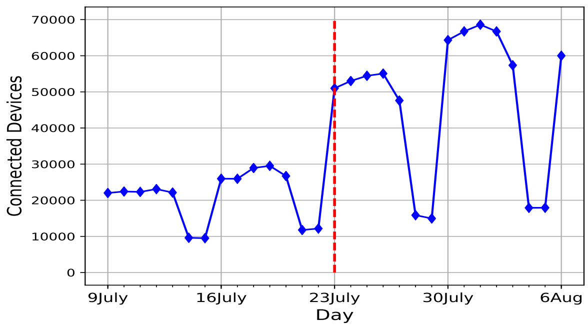
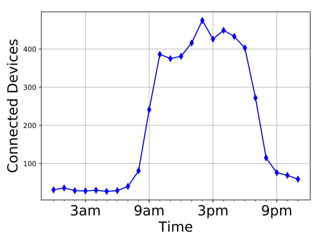


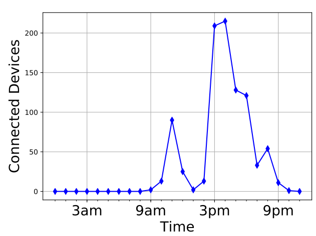
Fig. 5: Total connections made each day from 09-July-2018 to 05-Aug-2018.

B. Building Level Occupancy

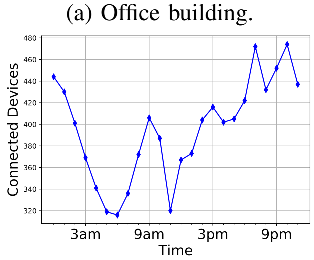
By mapping each AP to the specific building, we have plotted the one-day WiFi profile for different spaces on campus as shown in Fig. 6. In a office building (Fig. 6a), the occupancy depicts the typical working hours (10am-6pm) while the occupancy pattern demonstrates the timetable in a teaching space (Fig. 6b). The Fig. 6c shows that occupancy in one of the residential buildings on campus is higher during the evening and night times than the day time. The occupancy at gymnasium (Fig. 6d) peaks during 5pm-8pm and food court (Fig. 6e) shows it's peak hours as usual during 12pm-3pm. The Fig. 6f shows the occupancy in the library with 14 floors and it starts populating from 9am while peaking at 3pm - 4pm and then starts decreasing towards the end of the day.



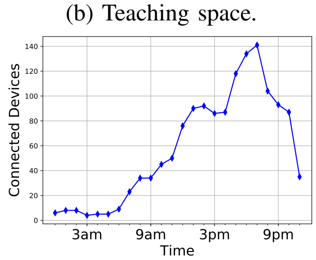
(a) Office building.



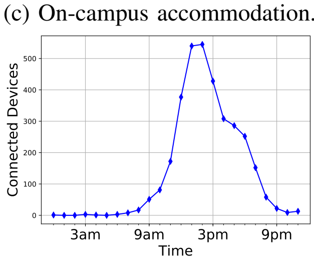
(b) Teaching space.



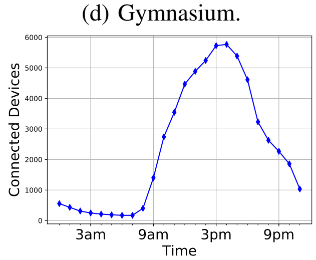
(c) On-campus accommodation.



(d) Gymnasium.



(e) Food court.



(f) Library.

Fig. 6: Number of connected devices to APs in different locations of our campus on a chosen day.

C. Applications

In a campus environment we have different communities who benefit from the spatial-temporal occupancy information. The students would be interested in knowing the crowding of restaurants, study spaces or gymnasium to schedule their routing accordingly. On the other hand campus estate managers are constantly looking for ways to enhance the on-campus facilities to improve student experience while raising the revenues through renting on-campus retail spaces. To this end, they may want to understand the foot traffic to find the ideal spaces to install new facilities such as learning spaces, restaurants and determine the pricing for retail spaces based on the popularity of the locations. The retailers aim to improve sales while looking for ways for peak-hour management such as optimizing the staffing and change of open hours etc. They are interested in temporal occupancy variations to identify the occupancy peaks around their store to help with decision making.

Similarly, ample of application can be developed by analyzing the occupancy using WiFi foot traffic and this work serves as the initial step to occupancy modeling in a university campus using WiFi connection data.

V. Conclusion

Occupancy monitoring in a campus environment can benefit variety of campus communities in different ways. In this paper we first compare performance of the two occupancy sensing methods; WiFi and Beam counters at room level. The results showed that WiFi sensed occupancy is comparable with the occupancy sensed by hardware beam counter sensors in terms of accuracy and even better when compared with the associated costs of installation and maintenance at campus-scale. Then we analyze WiFi device counts collected from our campus during 4 weeks period and add insights to the occupancy patterns and discuss the possible applications to benefit the different stakeholders on campus which we plan to implement in future work. Our study shows that metadata from existing WiFi AP network is a viable way of occupancy monitoring in a large university campus.

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