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Abstract

The case study presents a location-based data analysis framework for profiling visitor structure. In terms of recreational area management, understanding visitor structure is important. Traditionally, visitors monitoring with automatic counting devices has drawbacks of inaccurate visitors counting. In the case study, compared to automatic counting devices, we use Wi-Fi tracking as the main method to count visitors, which provides a fairly precise picture of visitor structure. Moreover, we deliver rich analytic functions in this framework and present the functionality with visitor data collected from the Guanyinshan Visitor Center. This framework not only standardizes visitor counting process but also facilitates a profound analysis of visitor structure.

Key Words: The Guanyinshan Visitor Center, Wi-Fi probe sensor, Media Access Control (MAC) address

Introduction

Knowing visitor structure has long been regarded as an essential component for recreational area management. To uncover the veil of visitor structure, visitor monitoring is a commonly used approach, and the information on visitor number is one of the most fundamental statistical metrics to evaluate the health of recreational areas. For many recreational area managers, visitor number is a main KPI for forming strategic and operational decisions, such as approving for visitor facility, conducting research on the trend of visitor preferences, and establishing SOP for visitor services. Thus, undoubtedly, making a reliable decision heavily relies on the accurate information of visitor numbers. Therefore, in order to achieve better decision quality, to standardize a systematic visitor monitoring scheme is indispensable.

Visitor monitoring evolution has been widely discussed in (Cessford et al., 2002; Muhar et al., 2002). As human counting is very labor-intensive, automatic counting devices are often regarded as a superb replacement. The important concept is that a systematic visitor monitoring is not simply grouping a collection of counting devices, but organizing these counting methods with a well-designed storage backend and various analytic features. Furthermore, standardizing measurements in different recreation zones is the key to provide objective judgements. If the visitor monitoring is established in traditional ad-hoc basis, not only the derived visitor number is inaccurate, but also huge installation cost is generated. For example, photoelectric counter, a light barrier device often used to count visitors when visitors pass the infrared sensors, is considering as an efficient counting device with low energy consumption. However, photoelectric counter is prone to misjudge the visitor number because the counting signal can be triggered by wildlife as well. In addition, it is impossible to infer the number of distinct visitors, so the visitor number tends to be inflated if a visitor is passed through these sensors multiple times or visitors walk in groups. From the view of visitor structure analysis, sample data without representativeness cannot be conducted with effective inferences, and the worst case is if the management decision is established based on the incorrect analysis, huge economic loss may be generated.

To overcome the aforementioned problems of traditional counting devices, Wi-Fi signals has been considered as a promising substitution to count visitors (Dionisio et al., 2016). Because most portable electronics devices use a unique Media Access Control (MAC) address to connect to public Wi-Fi spots, the MAC address turns into a suitable solution to avoid repeating calculation on visitor number.

In this project, we propose a location-based data analysis framework for recreational area management. By leveraging Wi-Fi signals as our main visitor counting scheme, we have the ability to eliminate duplicate counting and to standardize the counting procedure in different recreation areas. We believe most visitors nowadays usually use their own mobile devices, the number of MAC addresses within a given area will picture a fairly precise view of how many visitors are present at that recreational location. On top of the reliable visitor data source (location-based data), we provide rich analytic dashboards to profile visitor structure. The case study presents analytic dashboards with data collecting from the Guanyinshan Visitor Center. The future goal of this framework is to play as a foundation for various application extensions, such as visitor flow analysis and travel routes recommendation.

Literature Review

In this section, we first summarize related works of different visitor counting methods. Then, we focus on Wi-Fi based visitor monitoring to discuss possible applications and privacy issues.

2.1 Visitor counting methods

As conventional visitor counting consumes large amount of manpower resources, there are numerous ways of monitoring visitor counts from devices widely adopted, including image-based, photoelectric, Wi-Fi and Bluetooth based methods. Table 1 summarizes the pros and cons of different visitor counting methods.

While video counting is mainly applied in the field of surveillance, several studies were conducted on visitor counting (Ashkanani et al., 2015; Lefloch et al., 2008). However, these methods have inherent drawbacks. First, the coverage is limited, leading many blind areas to the monitoring. Second, the video counting results in degraded visual quality in certain scenarios such as insufficient lighting conditions and occlusions. Furthermore, using video counting raises privacy concerns. Photoelectric counting uses devices equipped with infrared sensors. For common scenarios, vendors usually install the sensors at the entrances to perform visitor counting (Arnberger & Brandenburg, 2002). When a person crosses the infrared beam, the counter is increased. It is widely used for visitor counting due to easy deployment. However, the sensor may underestimate visitor counts due to slow reading rate for crowded visitors. Besides, counts may be inaccurate in the case of getting in and out from the same person.

For wireless tracking methods, multiple threads of research leveraged Wi-Fi tracking and Bluetooth tracking (Antoniou & Lepouras, 2005; Kurkcu & Ozbay, 2017; Yoshimura et al., 2014) to detect visitors and estimate crowd density since both are ubiquitous technologies in human daily circumstances. Specifically, Wi-Fi based visitor counting can be divided into active and passive tracking (Scheuner et al., 2016). Active Wi-Fi tracking entails participants installing a specific software on their smartphones in order to perform people counting and additional analysis (Emery & Denko, 2007; Vinh et al., 2013). For passive Wi-Fi tracking, sensors receive Wi-Fi signals along with data packet to infer the number of visits. Several techniques are employed such as received signal strength indicator (RSSI), fingerprinting, probe request, and CSI (Putra, 2016). Since we adopt Wi-Fi probe sensor to count visitors in this project, we concentrate on the corresponding privacy issues and applications in the following.

Type	**Advantages**	**Disadvantages**
Manual counting	Well-trained operators can accurately count visitors within a short period of time.	It is labor-intensive, highly costly and prone to human error since human labors have limited attention span.
Photoelectric counting	Easy to deploy and low cost.	Visitor numbers may be inflated due to duplicate counts from the same person and cannot derive accurate counts in crowded conditions.
Video counting	Reach high accuracy with	Video counting suffers from

	computer vision algorithms such as segmentation.	limited coverage and privacy issues. Also, it does not operate well under insufficient lighting conditions and occlusions.
Wi-Fi based counting	High coverage and can reduce cost with lower number of sensors required.	Only Wi-Fi enabled devices can emit Wi-Fi probe requests with MAC address.
Bluetooth based counting	Robust, low power, and low cost.	Sensors can only detect Bluetooth enabled and discoverable devices.

Table 1. Summary of different visitor counting techniques

2.2 Visitor counting in recreational areas

For recreational area management, Muhar et al. provided an overview of visitor structure monitoring in recreational areas (Muhar et al., 2002). Other works discussed visitor management using national parks as case studies (Arnberger & Brandenburg, 2002; Gätje et al., 2002; McVetty, 2002). As for the corresponding applications, Schägner et al. devised a standardized reporting template for visitor counting studies and recreational visitor data sharing via a website for recreation monitoring (Schägner et al., 2017). Bielański et al. presented the application of GPS tracking for activity monitoring and can be practically used to improve visitor management strategies (Bielański et al., 2018). Also, visitor counting and flow can be analyzed using GIS tools to assist recreation planners and managers (Hinterberger et al., 2002).

2.3 Applications of passive Wi-Fi tracking

In terms of passive Wi-Fi tracking, many studies utilized the technique to tackle different problems. Some of them aimed at crowd counting while others specifically focused on pedestrian monitoring. Furthermore, there is widespread interest in human movement patterns such as frequent paths. Several researches aimed to understand social relationships of individuals and even some related works leveraged data mining and machine learning algorithms such as clustering and matrix factorization to further detect visitor groups. We list various applications and related studies in Table 2.

Applications	Studies

Crowd counting	(Bonne et al., 2013; Dionisio et al., 2016; Hong et al., 2018; Li et al., 2015; Vattapparamban et al., 2016; Weppner et al., 2016)
Pedestrian monitoring	(Kjærgaard et al., 2013; Kjaergaard et al., 2012; Kurkcu & Ozbay, 2017)
Human mobility	(Basalamah, 2016; Chon et al., 2014; Nunes et al., 2017; Traunmueller et al., 2018; Zhang et al., 2012; Zhou et al., 2018)
Social relationship	(Barbera et al., 2013; Hong et al., 2016; Wang et al., 2017)
Group detection	(Namiot, 2014; Shen et al., 2019)

Table 2. Summary of Wi-Fi tracking applications literature review

2.4 Privacy

Another line of research is concerned with privacy issues of using Wi-Fi based tracking. (Freudiger, 2015) showed that Wi-Fi probe requests are faced with the challenge of privacy threats and then summarized various attacks. Authors in (Kropeit, 2015) devised threat detection mechanism against the attack to mitigate the impact. Besides, according to (Han, Wang, & Pei, 2018), device manufacturers have implemented MAC address randomization in order to prevent users from identifying their traffic or physical location. However, with their own variants of MAC address randomization, real MAC address may be disclosed in certain circumstances (Martin et al., 2017; Vanhoef et al., 2016).

Methodology

In this pilot project, we aim to estimate the number of visitors in a particular area for each period and learn their behavior by tracking their visit frequency and duration. Because Wi-Fi is a cheaper and faster way to surf the internet, people who carries his/her personal mobile devices prefer to use Wi-Fi network instead of cellular network. We leveraged Wi-Fi sensors to capture the Wi-Fi probe signals generated by visitors' smartphones for the estimation and tracking analysis. According to IEEE 802.11, Wi-Fi probe signal is designed to broadcast periodically by a Wi-Fi enabled smartphone to scan for available nearby Wi-Fi Access Points (APs). The Wi-Fi probe signals (hereafter referred to as Wi-Fi probes) include the smartphones' MAC address such that an AP can respond and initiate a connection with the smartphones. The MAC address is a unique 12-character identifier (e.g., 0A:C0:D1:6E:81:0A) for a specific module of hardware, like the network adapter module in Wi-Fi devices. Since Wi-Fi probes are not encrypted, the Wi-Fi probe sensors can capture them without connecting to the smartphones. Note that the MAC address will be hashed and then store in the database for ensuring privacy compliance because each hashed MAC address cannot be directly associated with any personal information such as ID, real names, or phone numbers. The majority of people carry a mobile device whose Wi-Fi interface is enabled such that the count of unique MAC addresses tends to be proportional to the number of visitors. Therefore, we can estimate the number of visitors and track them to provide further analysis.

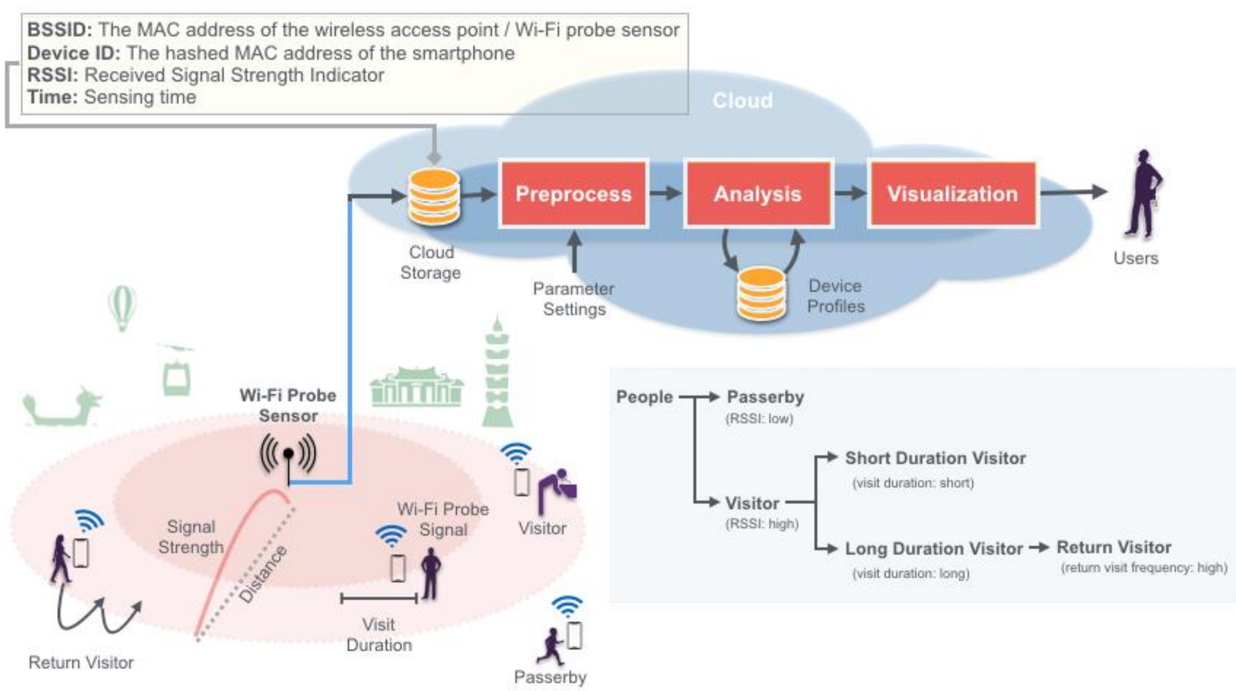

Figure 1. System Overview

An overview of our system is shown in Figure 1. The Wi-Fi probe sensor is set to capture probe signals. When Wi-Fi probe sensors capture probe signals, tuples of the BSSID, sensing time, RSSI, and the hashed MAC address are stored in the cloud for further processing. Wi-Fi probe signals can be captured even when the sender is several hundred meters away from the sensor.

Thus, in this project, we filtered out Wi-Fi probes with weak RSSI, so that we only collected data from close devices. Specifically, RSSI threshold can be derived for distance-based filtering. In addition, several metrics can be extracted, such as visit duration, and visit frequency. We can also identify the return visitors if a visitor had previously visited the place.

Finally, the interactive dashboards which show the visualization of analysis are provided to the users. Note that it is not necessary to install a specific application to collect data. Moreover, sensors are small and not expensive, so it is easy to install the sensing system in a new environment.

Results

Figure 2. The Guanyinshan map and the Guanyinshan Visitor Center where Wi-Fi probe sensors are installed.

In this section, we first introduce how we collect Wi-Fi probe data and then we demonstrate several analytic dashboards.

In this project, we collect probe request data from two Wi-Fi probe sensors installed at two sides of the entrance in the Guanyinshan Visitor Center located in New Taipei City to monitor visitors' activities from Oct. 1st to Dec. 31th in 2019. The received probes consist of multiple fields including hashed MAC address, RSSI, and sensing time. Then, the corresponding arriving time, leaving time and visit durations can be derived from the original data. To further understand visitor trend, we aggregate unique hashed MAC addresses per Wi-Fi probe sensor and per hour.

In the location-based data analysis framework, we have designed several analytic dashboards for providing possible insight. We convert data collected from Wi-Fi probes installed in the Guanyinshan Visitor Center into several systematic and logical visual elements, and we designed four filtering functions for users to choose their interested components. In these dashboards, we provide metrics for different visitor characteristics.

- Visit: mobile device is detected by a Wi-Fi probe within 0 ~ 15 meters per hour.
- Short duration visit: the visit duration is between 1 ~ 299 secs.
- Long duration visit: the visit duration is longer than 299 secs.
- Low return frequency visits: the total number of visits of a visitor whose total number of long duration visits is less than 3 times in the past month.
- High return frequency visits: the total number of visits of a visitor whose total number of long duration visits is larger than or equal to 3 times in the past month.

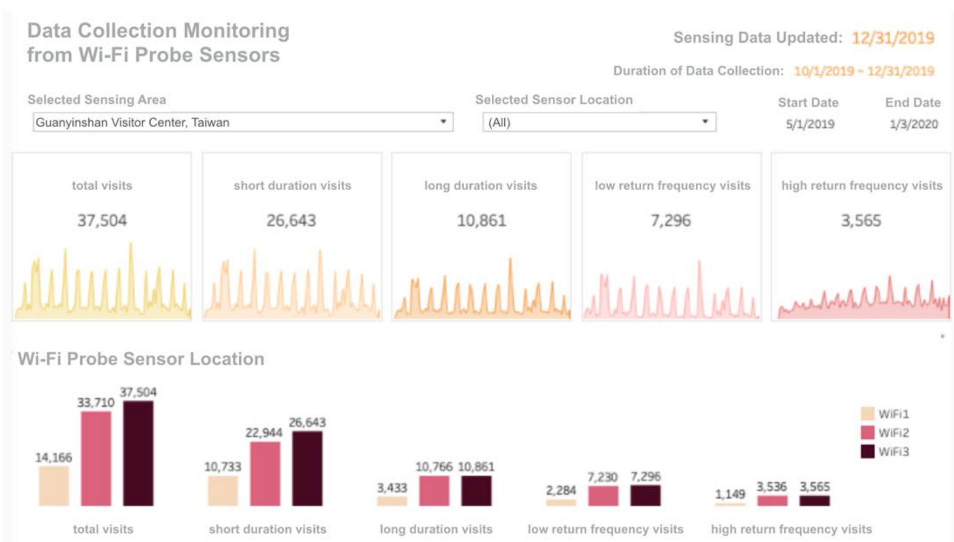

Figure 3. The dashboard of monitoring Wi-Fi probe data collection status.

Figure 3 presents four filtering conditions that can be used to select the most important data range and plot both time series patterns and histograms to the user. From the top-left, we can see selected sensing area, selected sensor location, start date and end date. The selected sensing area represents the area that the Wi-Fi probes have been placed and the selected sensor location is the actual position that a Wi-Fi probe has been installed. For example, data plotted in Figure 3 was collected from the Guanyinshan Visitor Center, denoted in selected sensing area, and we have placed two Wi-Fi probes near the service counter, denoted as WiFi1 and WiFi2 in selected sensor location. Start date and end date represent the date range that user is interested in. For example, the probing data was collected from Oct. 1st to Dec. 31th in 2019; however, user may only want to know the details about the visitor trend from Oct. 1st to Oct 15th because of some special events. In this case, user can update start date and end date with his/her preferred data range and view the details.

For counting the basic number of visits and visitors, we provide time series graph and histogram for these characteristics:

- the number of total visits,
- the number of short duration visits,
- the number of long duration visits,
- the number of low return frequency visits,
- the number of high return frequency visits.

In Figure 3, the upper part depicts the time series trend and actual counts for these visit types, and the lower part further group the number of each visit type by sensor location.

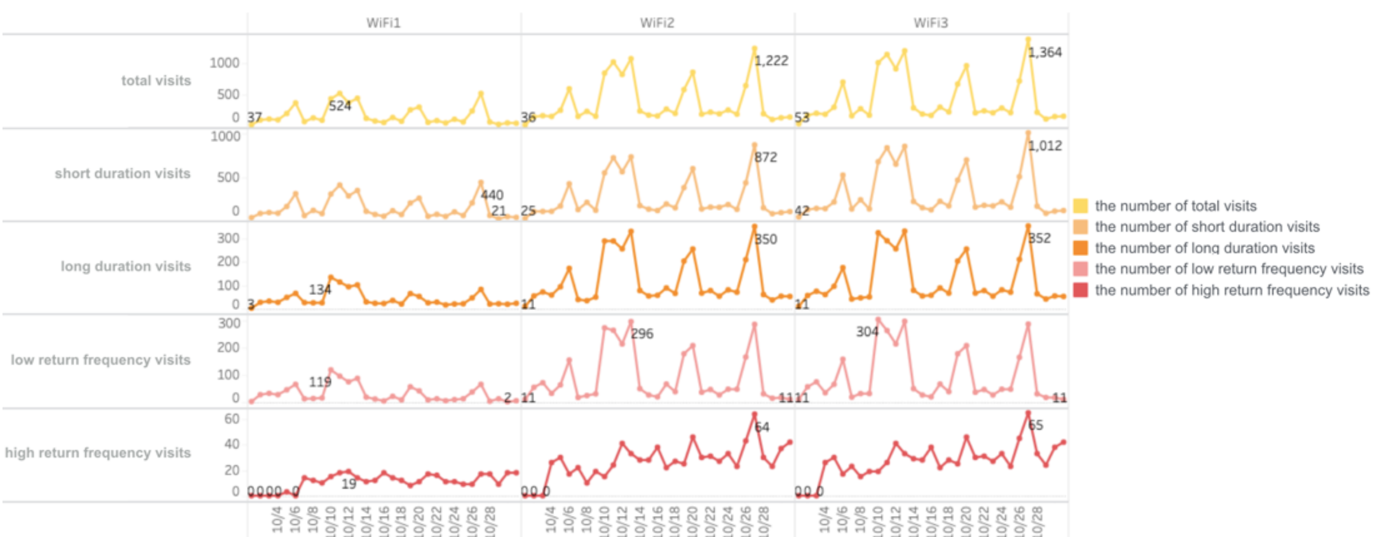

Figure 4. The dashboard of monitoring different type of visits trend in time-series.

Figure 4 is an extension view of Figure 3, which shows the time series pattern of each visit type with separated views of the sensor location. Figure 4 provides user a convenient view to compare the visit trend. For example, we can see that weekend usually has higher number of visits. Further, a pick number of visits occurred on Oct. 27th. According to the Guanyinshan Visitor Center, they have two groups of visitors carried by four tour bus on Oct. 27th. From the view of recreation area managers, they can easily compare the visitor trend with events that they hosted before; moreover, they can compare whether similar events bring comparable economic benefits in different recreation area.

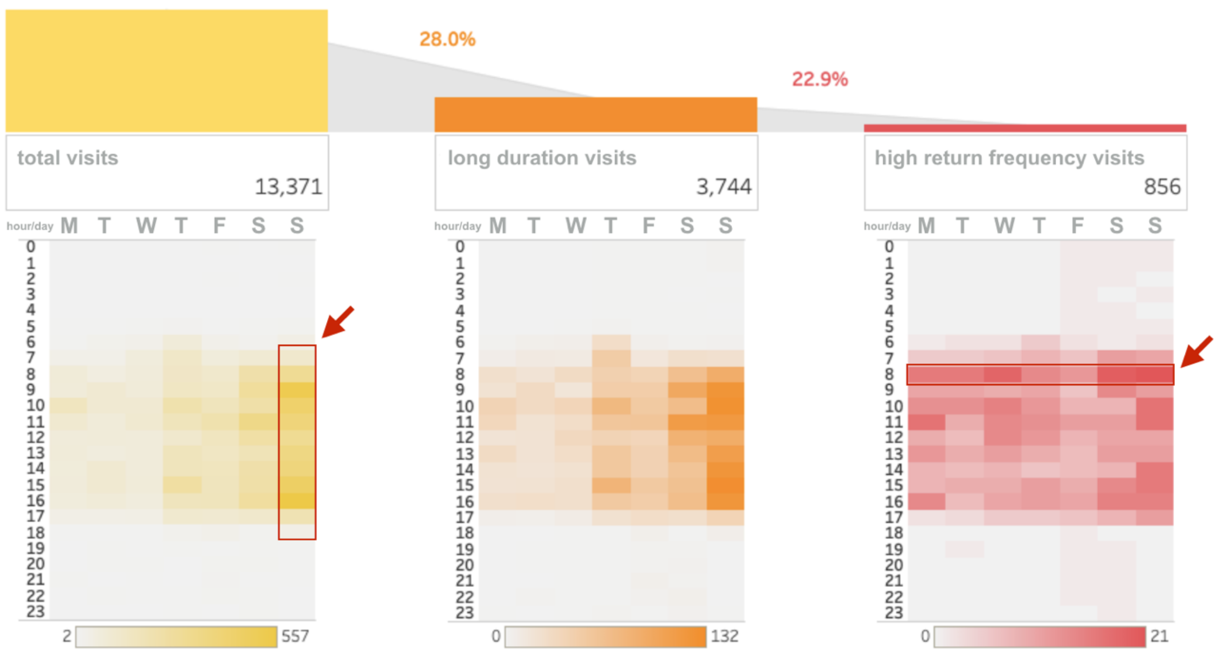

Figure 5. The dashboard of monitoring visitor structures by weekly.

Figure 5 provides a basic proportion view of the number of total visits, the number of long duration visits, and the number of high return frequency visits. For example, we can see that 28 % of total visits belongs to the long duration visits, and 22.9% of the long duration visits belongs to the high return frequency visits. For recreation area management, effective marketing strategy can be established based on the knowledge provided by Figure 5 to improve visitor adherence. The lower part of Figure 5 depicts heatmap of total visits, long duration visits and high return frequency visits. We can clearly see that Sunday has the highest number of total visits from eight o'clock to seventeen o'clock; while for those high return frequency visits, although high return frequency visitors do not have special preference visit day in a week, but they usually come to visit at eight o'clock everyday.

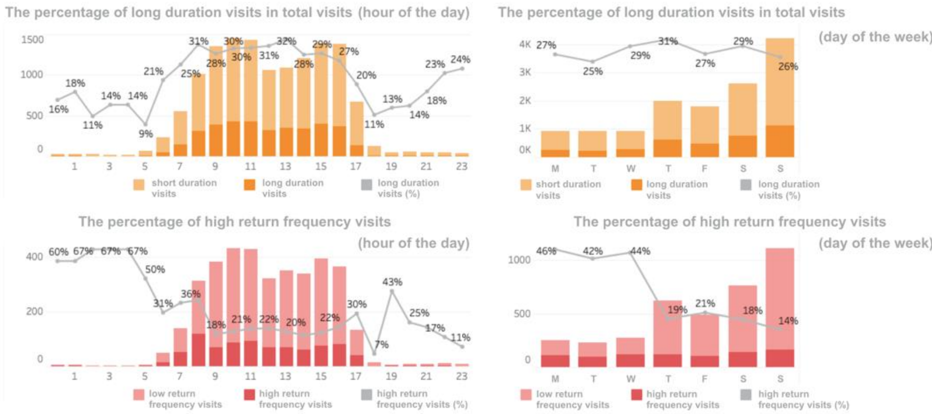

Figure 6. The dashboard of monitoring the actual composition of different visit types.

Figure 6 provides more visitor structure information that extended from Figure 5. Because we track visitor count from Wi-Fi signal, compared to traditional counting device, this system is able to provide more accurate visit count of each visit type and the composition of the visitor structure. Both Figure 5 and Figure 6 provide insights for recreation area manager to know their visitor structure, so that they can decide whether the future marketing strategy should focus on developing new visitors or strengthen relationships on high return frequency visitors.

Conclusion and Discussion

In this paper, we present a framework for analyzing visitor structure through visitor location data. Instead of using traditional counting devices, we leverage Wi-Fi signals to track hashed MAC address of visitors' devices. Because of the uniqueness of MAC address, our framework is able to depict visitor structure with finer granularity and higher accuracy for statistical estimations. Although the way of collecting data through Wi-Fi signals still has some limitations. For example, visitors' mobile devices fail to send signals to any probes because of its long probing intervals, or probes may loss tracking due to the shielding effect of the human body. These technical issues cause not every visitor can be exactly tracked even though he/she already carries a mobile device. However, we can mitigate these aforementioned problems by carefully installed multiple scanners along the planned route and filter out abnormal device records at the analytic phase.

Finally, we also demonstrate several dashboards for users, such as recreation area managers, to discover key insights. We believe various applications can build upon this framework with these results. For example, we can discover the pattern of visitor flows through frequent path mining, or link visitor activities with social relationships and predict visitor behavior through machine learning. In the future, relying on empirical research of mobile usage data (Chou et al., 2018), we will work toward exploring mobility of crowds from collected Wi-Fi probe data for tourism management and further leverage community detection to distinguish different travel party size for better understanding tourists' movement patterns and behaviors (Zhao et al., 2018).

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