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A LOW-COST WI-FI–BASED SOLUTION FOR MEASURING HUMAN QUEUES

Creating devices or systems that can leverage computationally rich environments to support day-to-day interactions between humans and computers is the goal of mobile computing and communication. The increasing use of mobile devices and their data-intensive apps has generated extensive opportunities to monitor and optimize real-world processes through network traffic and corresponding characteristics. For example, research has already shown that we can use cellular call data records and signal traces to understand patterns of large-scale transportation [1] and the level of congestion on roadways [2], respectively. Likewise, ubiquitous wireless infrastructures (e.g., Wi-Fi and Bluetooth) not only provide convenience in communication, but also enable novel applications, such as indoor localization and user authentication. In addition, we have found that the strength of wireless signals from the Wi-Fi traffic consumed by mobile devices can be utilized to perform fine-grained monitoring on a daily common process, i.e., human queues.

Human queues are usually formed by people who are waiting for services in long lines. Such familiar and frustrating occurrences often happen at retail stores, banks, theme parks, hospitals, and transportation stations. Based on our findings, we have proposed a novel solution for estimating the wait time of human queues by leveraging the existing Wi-Fi infrastructures and traffic from the mobile devices used by people waiting in the queues. The biggest advantage of our Wi-Fi based solution is that it can work with complicated queue patterns under various real-world scenarios without deploying a specialized infrastructure or incurring manpower overhead. Furthermore, our solution can accurately estimate the wait time of human

queues based on the Wi-Fi traffic consumed by a small fraction of people in line.

MEASURING HUMAN QUEUES

A typical human queue process contains three important time periods: 1) the *waiting period* spans between the time of arrival and receipt of service; 2) the *service period* is the time for service related activities, such as paying for services, accepting treatments, and waiting for items; 3) the *leaving period* is the time during which people exit the queue. We note that our concept of human queues are loosely defined, people in queues are not restricted to be in a line but could flexibly stay in a waiting room, and they might not be served in a strict first-in first-out order.

Real-time quantification of the waiting and service periods are the key information to optimize the process of human queues in various industries. For example, a manager in a coffee shop may want to change the staffing to use skillful baristas as opposed to simply adding staff, when the waiting period grows longer due to increased demands for espresso drinks compared to other items. Similarly, a hospital emergency department might want to arrange experienced nursing staff to help with triage when waiting times for patients become too long. The security departments at airports could assign skillful screeners to checkpoints experiencing abnormally long delays to reduce service and wait times of the queue.

In addition, not only service providers but customers can also benefit from complete queue measurements. For example, knowing when customer lines in banks are expected to be shorter could help a customer to adjust his/her agenda. Visitors in a Walt Disney World Theme Park may reschedule their trips based on the timely report of the queue length at each attraction to make full use of their limited visiting period.

In order to obtain the measurements of human queues, existing solutions have utilized cameras [3], special sensors (such as infrared [4] or floor-mat sensors [5]), and Bluetooth monitors [6]. However, cameras always have issues with public privacy, and special sensors even Bluetooth monitors usually require multiple devices at different locations to fully monitor a long queue, which involves extra installation and system costs. Moreover, these solutions yet are too coarse-grained to differentiate between the waiting and service time with single device.

A LOW-COST APPROACH LEVERAGING WI-FI SIGNAL

We have found that, by using a single Wi-Fi monitor at the end of a human queue, the received signal strength of Wi-Fi packets sent by mobile devices in the queue has a unique pattern corresponding to the distance between the mobile devices and the Wi-Fi monitor, which can be utilized for measuring human queue. By intuition, the received signal strength slowly increases when a user moves toward the service point with his/her mobile device during the waiting period. When the person starts to receive the service, the signal strength should be the strongest and keep stable for the entire service period. Finally, after receiving the service, the received signal strength dramatically drops as the person exits the queue and moves away from the service point.

Figure 1 presents the received signal strength (RSS) trace of a smartphone in a queue collected from a single Wi-Fi monitor at the service desk in a coffee shop. The captured RSS trace reflects the aforementioned pattern of the distance between the mobile device user and the Wi-Fi monitor placed at the service desk. We foresee that such Wi-Fi monitor can be integrated with Wi-Fi access points that are already popular in retail stores, hospitals, banks, and transportation stations.

IMPLEMENTATION CHALLENGES

Because the multipath, shadowing, and fading effects to a wireless signal are dynamic due to the movements of the wireless device and changing environments, it is a very challenging task to accurately identify the time points of the start and the end of the service. We hereby summarize the major challenges to implement our system as follows.

Tracking queues with a low-infrastructure approach. Our approach only requires a single Wi-Fi monitor at the end of the queue, which cannot uniquely determine the mobile users' positions. Thus our low-infrastructure solution should be independent of localizing mobile devices, and only estimate the parameters of the queue based on the unique signal patterns presented in the mobile devices' Wi-Fi traffic.

Embracing noisy real environments. Even though the distance between the mobile device and the Wi-Fi monitor dominates the received signal, the RSS is still far from stable in typical indoor environments. The RSS is really noisy mainly because it is affected by various factors, including user movements, holding styles, vibrations of mobile devices, changing surrounding obstacles, signal interferences, and multi-path effects (Rayleigh fading). In addition, the RSS of Wi-Fi signal is significantly attenuated by human bodies in queues. Thus, our system should be designed to cope with noisy signal readings using practical approaches.

Identifying queue-related signal traces. The received Wi-Fi signal traces from mobile devices may contain RSS trends similar to that related to queue process. In order to automate our queue measuring solution, an effective data-calibration mechanism is required to identify the segment of the RSS trace including only the important time periods of the queue process.

SYSTEM OVERVIEW

Figure 2 shows the flow of our system. There are three main subtasks in our system: data calibration, integration of multiple antennas, and queue parameter determination. Our system starts to collect the RSS measurements from a mobile device when the Wi-Fi monitor discovers that the mobile device enters the queue. The collected RSS trace is first processed by the data calibration, which simultaneously removes high frequency noise in the RSS measurements and preserves the unique signal pattern embedded in the raw RSS trace. Then the system further identifies the segment of RSS measurements that contains queue related time periods.

Next, our system integrates RSS measurements from multiple antennas to filter out signal outliers and obtain a reliable Wi-Fi signal trace. Based on the fact that many commercial Wi-Fi access points are already equipped with two or more antennas, we design the subtask that combines the selected RSS traces from two antennas in the Wi-Fi monitor to generate a new signal trace, which fortifies the unique signal pattern associated with important time periods of a human queue process.

Finally, the queue parameter determination implements a Bayesian Network scheme based on unique queue-related features to infer the critical time points that separate the waiting, service, and leaving periods. The critical time points, namely the beginning of service (BoS), leaving point (LP), and end of leaving (EoL), are used to estimate the queue parameters, including the length of waiting and service periods. In particular, our system utilizes the BoS and the starting time of the trace to estimate the waiting period; whereas the service period is the time interval between the BoS and LP, and the leaving period is the time interval between the LP and EoL.

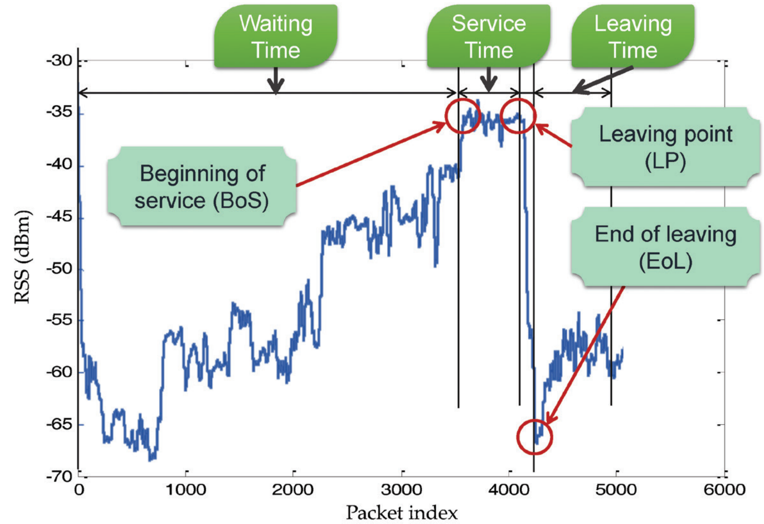

FIGURE 1. Illustration of the unique distance-related pattern extracted from the Wi-Fi signal strength of a smartphone observed by a monitor at the end of the queue.

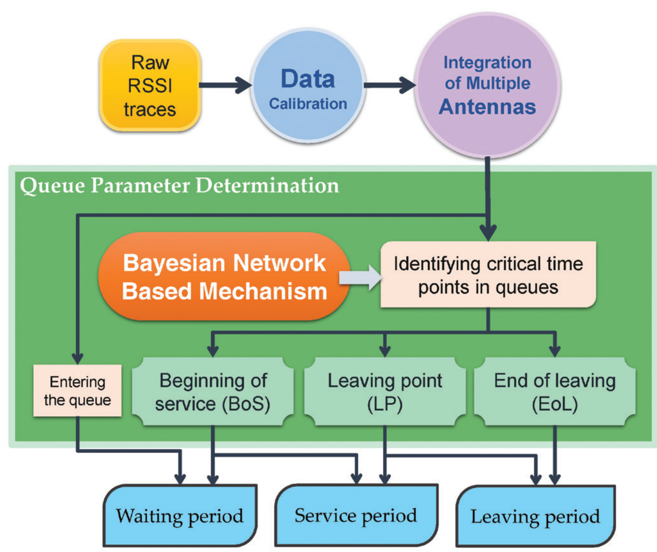

FIGURE 2. Flow overview of our queue-monitoring system.

BAYESIAN NETWORK–BASED MECHANISM

We developed a Bayesian Network scheme for our system to identify the critical time points in a human. In particular, we identified three features extracted from the RSS trace associated with the leaving period as illustrated in Figure 1:

- the leaving period has the longest consecutive negative-slope segments of the selected RSS trace;
- the received signals before the leaving period are stable with the highest amplitude of the selected RSS trace; and
- the leaving period experiences the largest decrease of the signal in the selected RSS trace.

The Bayesian Network scheme first identifies all the RSS segments containing continuous positive or negative RSS slopes in the RSS trace, and uses them as inputs to run BoS and LP estimation using a naive Bayesian classifier. Specifically, we modelled BoS and LP as two parent nodes in the

FIGURE 3. Experimental evaluation in real environments: (a) the coffee shop environment (b) and the airport environment.

Bayesian Network and define six child variables (Boolean random variables) based on the aforementioned features embedded in the RSS trace when the mobile device is used in a queue:

- **R:** The average RSS within the service period is usually the highest. R = 1 when the mean RSS before a specific segment of continuous negative slopes is the highest of all, otherwise R = 0.
- **S:** The RSS within the service period is stable. S = 1 when the variation of RSS within a window W before a segment of continuous negative slopes is smaller than a threshold _, otherwise S = 0.
- **LLP:** The leaving period happens after the service period, which has the strongest RSS. LLP = 1 when the starting time of a specific segment of continuous negative slopes is later than the time with the highest RSS value, otherwise LLP = 0.
- **CLP:** The change of RSS after the leaving period usually exhibits the most significant decreasing trend. CLP = 1 when the average slope of a specific segment of continuous negative slopes is the smallest of all, otherwise CLP = 0.
- **LBoS:** The waiting period happens before the service period, which has the strongest RSS. LBoS = 1 when the end time of a specific segment of continuous positive slopes is earlier than the time with the highest RSS, otherwise LBoS = 0.
- **CBoS:** The change of RSS before the service period usually exhibits the most significant increasing trend. CBoS = 1 when the average slope of a specific segment of continuous positive slopes is the largest of all, otherwise CBoS = 0.

The naive Bayesian classifier examines the ending time of each input segment with continuously positive slopes and considers the ending time to be a BoS when the segment maximizes the posterior probability under the condition of BoS. Similarly the classifier examines the starting time of each input segment with continuously negative slope and considers the starting time to be a LP.

EVALUATION

To understand whether there are sufficient Wi-Fi users in human queues to facilitate queue measurements, we investigated the density of mobile devices that use WiFi in a coffee shop for one month. We placed a Wi-Fi monitor close to the service desk to passively monitor Wi-Fi packets sent by surrounding mobile devices, and an empirical threshold (-45dBm) is used to determine whether a mobile device is within the queue. We found that more than 30 percent of customers were using Wi-Fi service while waiting in line for coffee, which indicates that it is feasible to leverage Wi-Fi traffic from mobile devices used in the queue for human queue measurements.

We further respectively collected 72 and 54 RSS traces in two real environments, a coffee shop and an airport over one month, with volunteers holding different types of smartphones in the queues. The smartphones we used in the experiments span the HTC 3D, HTC EVO 4G, and Nexus One. When using the Bayesian Network scheme, our system provides consistently low estimation errors in both environments: the LP and BoS estimation errors are less than 8s for both the coffee shop and airport. Whereas the waiting and service times estimation achieves low average errors less than 8s in coffee shop and about 5s and 10s in the airport, respectively. The standard deviation of estimation errors in both environments is around 3s to 7s. This indicates that our system is effective in measuring human queues with high accuracy using only a single-point Wi-Fi signal monitor and a sample of phones in the queue.

As a conclusion, we designed a low-infrastructure system for measuring human queues, which could enable a wide range of applications including bottleneck analysis, shift assignments, and dynamic workflow scheduling. We foresee that the Wi-Fi-based solution for real-time human queue monitoring will quickly emerge along with the improvements of its accuracy, compatibility, and security. Compared to the approaches using cameras or special sensors, our system could provide accurate real-time measurements of human queues by leveraging existing Wi-Fi access points without adding one single additional monitoring device. ■

REFERENCES

[1] S. Isaacman et al., "Human Mobility Modeling at Metropolitan Scales," *Proc. 10th Int'l Conf. Mobile Systems, Applications, and Services* (MobiSys 12), 2012, pp. 239–252.

[2] G. Chandrasekaran et al., "Vehicular Speed Estimation Using Received Signal Strength from Mobile Phones," *Proc. 12th ACM Int'l Conf. Ubiquitous Computing* (Ubicomp 10), 2010, pp. 237–240.

[3] V. Parameswaran et al., "Design and Validation of a System for People Queue Statistics Estimation," *Video Analytics for Business Intelligence*, vol. 409, 2012, pp. 355–373.

[4] U. Stilla et al., "Airborne Monitoring of Vehicle Activity in Urban Areas," *International Archives of Photogrammetry and Remote Sensing* 35, no. B3, pp. 973-979.

[5] D. Bauer et al., "Simple Sensors Used for Measuring Service Times and Counting Pedestrians," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2214, no. 1, 2011, pp. 77– 84.

[6] D. M. Bullock and et al., "Automated measurement of wait times at airport security," *Transportation Research Record: Journal of the Transportation Research Board 2177*, no. 1 (2010): 60-68.