A Tool for Checking Attendance of Students in Classroom Automatically

Prof. Taekyoung Kwon, Seoul National University

Ted "Taekyoung" Kwon is a professor with Department of Computer Science and Engineering, Seoul National University (SNU). Before joining SNU, he was a Postdoctoral Research Associate at University of California Los Angeles and City University New York. He obtained BS, MS and PhD at SNU in 1993, 1995, 2000, respectively. During his graduate program, he was a visiting student at IBM T.J. Watson Research Center and at University of North Texas. He was a visiting professor at Rutgers University in 2010. His research interest lies in future Internet, indoor localization, network security, and wireless networks.

Mr. Myungchul Kwak, Seoul National University

I'm a Ph.D student at the Dept. of Computer Science and Engineering, Seoul National University, Seoul, Korea. (Mar. 2012 - Current). Before joining SNU, I obtained B.S. in Dept. of Computer Science and Engineering, Hanyang University, Ansan, Korea.

Mr. Junghwan Song, Seoul National University

TBD

Mr. Selin Chun, Seoul National University

•M.S. in Dept. of Computer Science and Engineering, Seoul National University, Korea, 2015.3 - current
•B.S. in Dept. of Computer Science and Engineering, Seoul National University, Korea, 2011.3 - 2015.2

Prof. Seokho Chi, Seoul National University

Associate Professor at the Department of Civil and Environmental Engineering at Seoul National University in Seoul, Korea. He has worked on construction management, occupational health and safety in construction, disaster management, and IT applications in construction specifically using advanced technologies including Big Data analysis, PMIS (Project Information Management Systems), video mining, and smart sensing.

A Smartphone-based Tool for Checking Attendance of Students in Classroom Automatically

Myungchul Kwak, Junghwan Song, Selin Chun, Taekyoung (Ted) Kwon, Seokho Chi

{mckwak,jhsong,slchun}@mmlab.snu.ac.kr, {tkkwon;shchi}@snu.ac.kr

Seoul National University

Abstract

We design and implement a software tool running in a smartphone to check the attendance of enrolled students automatically. The students need to install the application to their smartphones. The challenging issue in designing this software tool is that we need to find out whether a student is inside or outside the classroom in an automatic fashion. For this purpose, the application in a student's phone will measure the current signal strengths of Bluetooth devices around the classroom, which are reported to a server running the software that checks the student attendance. Then, the server decides whether the student is located inside or outside the classroom by analyzing the signal strengths. The comprehensive measurements of WiFi and Bluetooth strengths reveal that the smartphone's WiFi scanning consumes much more energy than BLE scanning, and the received signal power of a WiFi beacon tends to vary substantially due to interference and fading. That is, WiFi signal strengths may not be able to localize the student at the granularity of a classroom. If we can deploy Bluetooth devices, we can adjust their transmission power levels, which helps to figure out whether the student is located within or out of the classroom (so-called geofencing). By leveraging Bluetooth devices, we can achieve significantly better geofencing performance.

Introduction

The location of a user is one of the most essential context data to provide intelligent services, such as navigation, health care, and marketing, which are collectively called location based services (LBSs). Recently, thanks to the diffusion of smartphones, the demand for and usage of LBSs are increasing. However, in the case of indoor spaces where GPS signals are not available, alternative technologies to infer the locations of users are needed. Modern smartphones have various sensors like WiFi, Bluetooth, inertial sensors like accelerometer and magnetometer. Thus, there have been many efforts to design the effective indoor localization systems and services by exploiting such sensors.

LBSs are also needed in education markets. Most students have smartphones, and mostly spend their daily lives in the indoor spaces (e.g., campus buildings and classrooms), and thus there are chances to provide more customized and intelligent educational services based on the information of students' locations. There have been many general-purpose LBS solutions like navigation systems[3,4,6], or location-aware health care solutions[5,8,9]; however, LBSs specialized for campus areas are rare. Motivated by this, we seek to design a software tool to check the attendance of students.

Geofencing with Bluetooth technology

We design a software tool to check the attendance of students in a classroom, which is also called "geofencing", which means we should be able to find out whether a user is within or outside of an area of interest[7]. To substantiate the tool, we exploit one of the wireless communication interfaces of a smartphone to build a virtual fence that delineates the boundary of the area of interest. The received signal strength (RSS) of a wireless signal becomes weaker as the distance between a student and a reference node (i.e. WiFi AP, Bluetooth beacon) increases. If the distance goes beyond a certain threshold, the signal cannot be detected at all. We thus can carry out "geofencing" around the classroom by observing the RSS of a wireless signal, and can also control the range of geofencing by adjusting the signal transmission power (Tx power) of a reference node.

In general, recent smartphones have multiple wireless interfaces; cellular (3G or LTE), WiFi, Bluetooth Low Energy (BLE), and near field communication (NFC). Each technology has different characteristics, and thus we may have to use multiple interfaces for geofencing purposes. In case of a cellular network interface, we cannot know the exact location of a base station (as a reference node) and cannot easily access to the relevant information like the Tx power. And in case of NFC, its communication range is too short to be used for geofencing. Therefore, we exclude these two technologies for geofencing purposes.

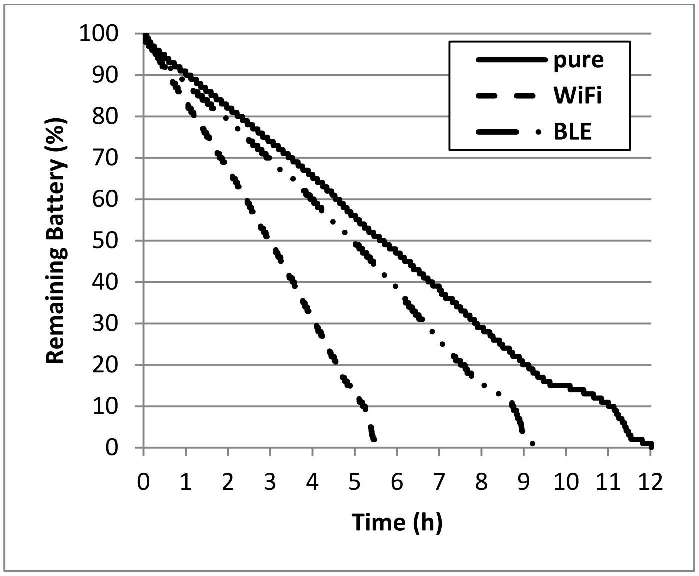

Figure 1. The remaining energy level of a smartphone is plotted over time when either of BLE and WiFi interfaces is turned on for scanning purposes.

In case of WiFi, there are several weaknesses of WiFi signals over BLE signals. First, WiFi consumes energy more quickly than BLE due to its scanning mechanism. Fig. 1 shows how fast the remaining energy of a smartphone decreases as it continuously collects the beacon frames of access points (APs) to obtain their RSS values. WiFi scanning spends 1.5 times more energy than BLE scanning, and nearly 2 times than the “pure” scenario in which the smartphone is not scanning. This result comes from the different numbers of communication channels between WiFi and BLE, which the smartphone has to scan. The smartphone has to scan at least 13 WiFi channels, while there are only 3 advertising channels in the BLE specification. This constraint also affects the duration of WiFi scanning. In most smartphones, a WiFi scanning period is about 3~4 seconds, whereas a BLE scanning period can be less than 1 second.

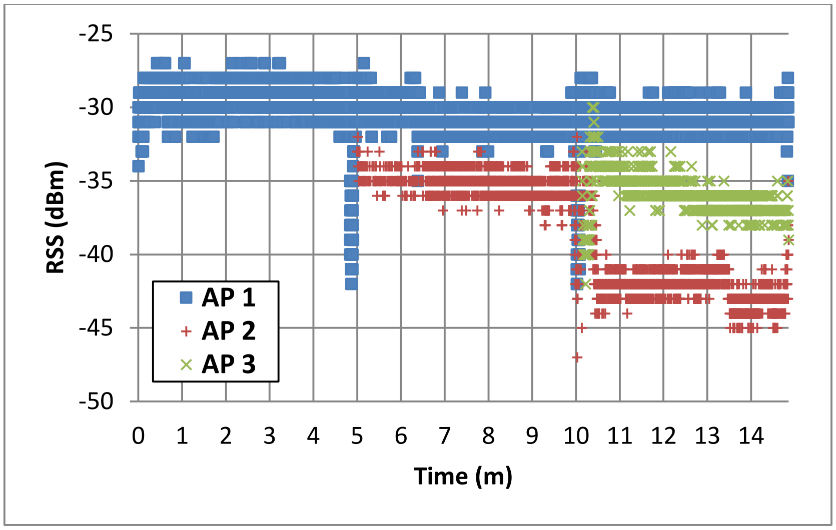

Figure 2. RSS values of the three APs changes over time as each AP is turned on at 0, 5, 10 minutes, respectively.

Moreover, most WiFi AP vendors adopt a dynamic Tx power control algorithm to avoid the interference between APs. Fig. 2 plots the change of the RSS values of the three APs nearby when Aps are successively turned on one after another at 5 minute intervals. The result shows that the Tx power of an AP can be dynamically changed without manual adjustment. This is why we cannot rely on WiFi to design a geofencing mechanism. And lastly, Apple iPhones do not officially support the application programming interfaces (APIs) for WiFi scanning operations. That is, we cannot get RSSs of WiFi APs with iPhones. Consequently, we exploit BLE signals to design our geofencing system.

BLE Signal Measurements

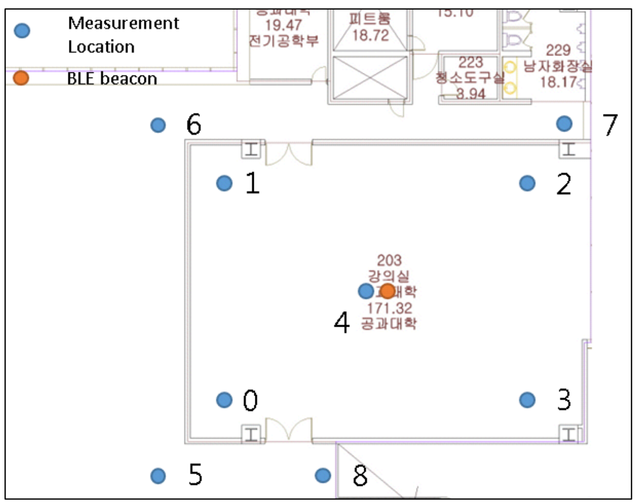

Figure 3. The floorplan of the target space as well as the locations of measurement points and BLE beacons is shown.

This section describes the comprehensive measurements of BLE signals, which is the basis for designing the class attendance checking system. We seek to obtain an insight from the results. For data collection, we choose a moderate size classroom (9m by 12m) in our campus building as a target space, and select 9 measurement locations around the classroom as shown in Fig. 3. We then deploy a commercial class 2 BLE beacon that has a moderate communication range, and collect the RSS values in each location for a minute. Note that the deployment location of the BLE beacon is the center of classroom ceiling (depicted as a red dot), to mitigate the fading and human body effect[31,32] by minimizing the shaded area of the BLE signal.

Basically the BLE signal becomes undetectable as the distance to the BLE beacon increases. Also, its signal strength is degraded by wall attenuation[2]. With this knowledge, we can infer whether a student (or her smartphone) is located inside or outside the classroom by observing the change of an RSS. Thus finding the optimal Tx power level which can cover the entire area of a classroom is an important step. To find out the optimal Tx power, we collect RSS values from inside (points 0 ~ 4 in Fig. 3.) and outside of the classroom (points 5 ~ 8 in Fig. 3) while varying the Tx power. Also, we adopt non-line-of-sight (NLOS) and line-of-sight (LOS) positions to observe the human body effect on the RSS of BLE. In NLOS positions, there is a human body between the beacon and the smartphone while collecting. Note that the available Tx power range of our class 2 BLE beacon is between -23 dBm and 4 dBm, and the beacon advertising rate is 1 Hz.

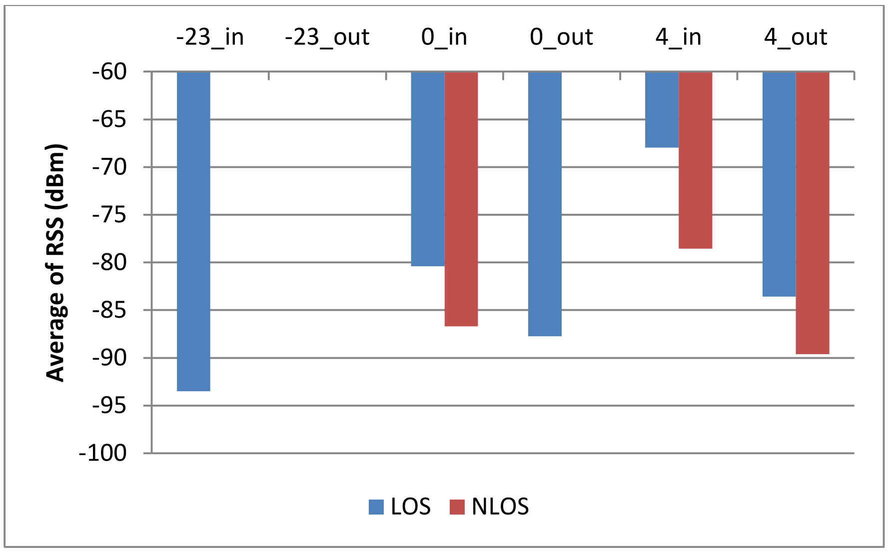

Figure 4. RSSs of BLE signals for each Tx power are averaged over positions inside and outside the classroom, respectively, which are denoted by _in and _out, respectively.

Fig. 4 shows the average RSS of each case. Each label in the x-axis means (i) one of adjusted Tx powers and (ii) whether the measurement location is inside or outside the classroom. When the Tx power is -23 dBm (min. Tx power), the RSS is too weak and hence the BLE beacon frame is not observed in NLOS positions. It means that if the classroom is crowded or a student puts the smartphone in her pocket, her attendance cannot be checked even if she is in the classroom. We define this situation as a ***false negative*** case, -23 dBm is too weak to avoid false negative. In case of 4 dBm (max. Tx power), RSSs are clearly observed at every location. However, BLE beacon frames reach outside the classroom even when the smartphone is located in NLOS positions, which will negatively affect the geofencing performance. In such circumstances, ***false positive*** cases will happen, which means the attendance of a student is checked even if she is located outside the classroom.

Consequently, we need to find out the appropriate Tx power (of a BLE device) to avoid both false negative and false positive cases. It turns out that setting the Tx power to 0 dBm can reduce both false negative and false positive cases. In case of 0 dBm, although the beacon frames may reach a student outside of the classroom in LOS positions, they become undetected quickly as the distance to the beacon increases.

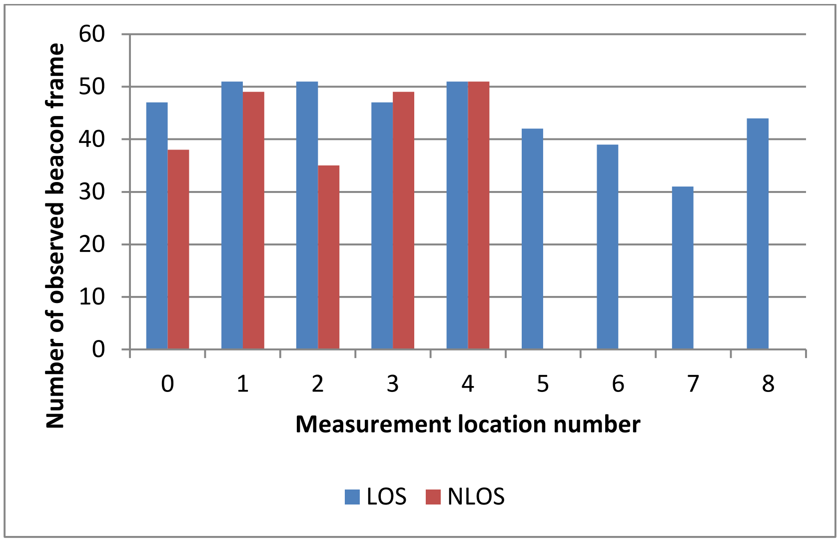

Figure 5. Number of observed beacon frames at each location is plotted when the Tx power is set to 0 dBm.

As mentioned above, the RSS of a BLE beacon is unstable, and thus we measure the number of observed beacon frames at each location as shown in Fig. 3. Fig. 5 plots the number of observed beacon frames for one minute duration at each location. Considering the worst case (location number 2), where the number of observed beacon frames for one minute is 35, we can deem that the student is inside the classroom with high probability if the rate of receiving beacon frames is above 0.5.

Next step is, then, solving the false positive issue which can occur outside the classroom at LOS positions. Checking the attendance based only on the rate of observed BLE beacons might be risky when a student stands right next to the wall outside the classroom and places her smartphone in an LOS position. For this, we leverage an entry detector, which is typically based on an infrared sensor. The entry counter can count the number of people in the room by detecting the entry or exit of each person. We implement a similar scheme by using a BLE beacon, not the infrared sensor.

$$\boldsymbol{RSS\ difference = RSS_{inside} - RSS_{outside}}$$

To detect the entry or exit (of a student) through the door of the classroom, we simply install another BLE beacon in a proper position outside the classroom, and trace the difference of two

RSS values from inside and outside beacons. The difference of RSSs is calculated by the RSS of the inside beacon minus that of the outside beacon as expressed by the above equation. If the difference increases (above 0), the student is considered to enter the classroom, and if the difference decreases (below 0), she is deemed to go out of the classroom.

Figure 6. Locations of two BLE beacons and the target door are shown in the floor map.

The proper position for a BLE beacon outside the classroom is a point that covers all possible trajectories to the door. Also, the distances between both of the beacons and the door should be very close, so that the RSS difference becomes almost zero when passing through the door. Thus we locate the position of the outside beacon in our experiment as shown in Fig. 6.

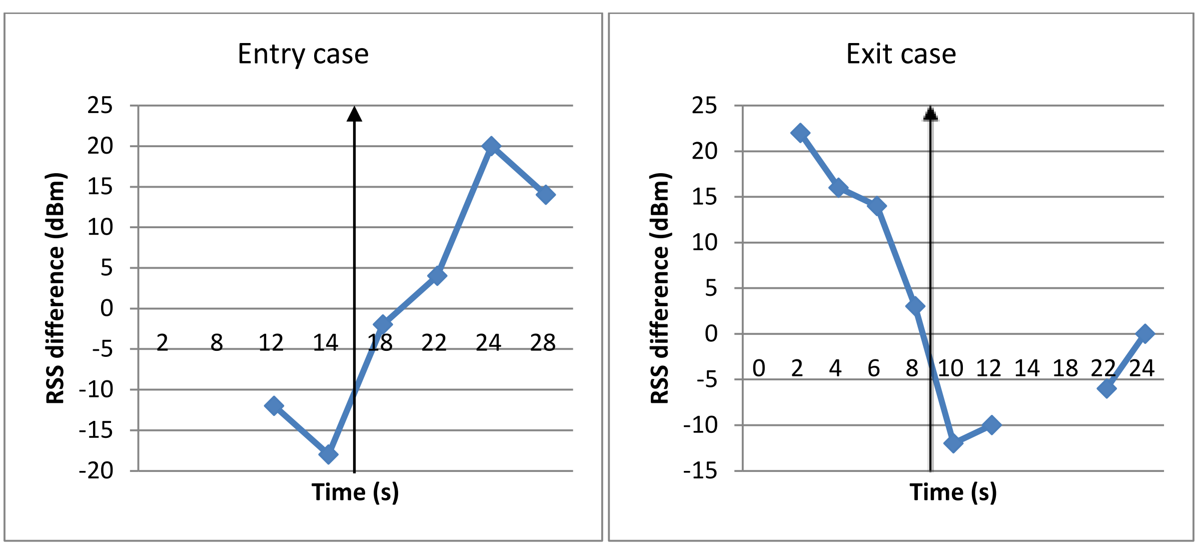

Figure 7. The difference in RSS values from the insider and outside beacons varies as a student enters and goes out of the classroom.

We set the Tx power of the outside beacon to 0 dBm (or 1mW), and thus it can cover the area of a similar size to the one covered by the inside beacon. Since the beacon advertising time of each beacon is not synchronized, and also their signals experience fading independently, the beacon frames are received by the smartphone at different moments. To solve this issue, we compute the average difference between the RSSs of the inside beacon's frames and those of the outside beacon's frames during the last 5 seconds. Fig. 7 shows the change of the RSS difference when entering or exiting through the door, and the black vertical line means the time when the student passes the door. The RSS difference clearly shows the increasing/decreasing patterns when the student enters or exits through the door, and becomes almost zero when the student passes through the door.

System Design

This section describes the overall system design of the attendance checking tool and the algorithm details.

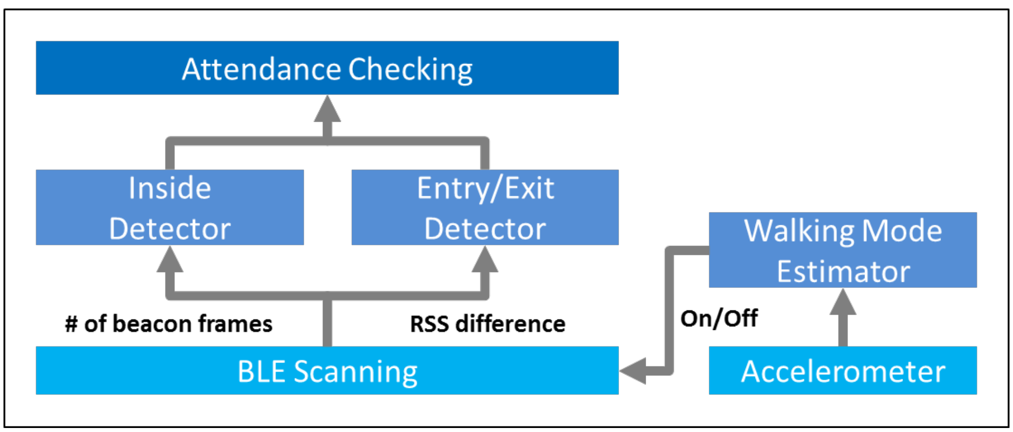

Figure 8. Our attendance checking tool is based on sensors: the BLE and the accelerometer. From the two sensors, we can figure out whether a student is moving, inside/outside the classroom and so on.

Fig. 8 shows the building blocks of the proposed attendance checking system. Based on the intuitions from the earlier measurements, we design two sub-components to check the attendance; an inside detector and an entry/exit detector. The inside detector decides whether a student is inside or outside of a classroom based on the rate of observed beacon frames, and the entry/exit detector is responsible for detecting the student's entry or exit through the door based on the change of the RSS difference.

In case of the inside detector, if the rate of observed beacon frames is over a threshold in a certain period of time, it deems that the student is inside the classroom. This threshold rate is defined as 0.5 based on the above measurement, and the length of time period is set to 10 seconds. That is, the inside detector infers that the student is inside the classroom if the number of observed beacon frames is over 5 for the last 10 seconds. Note that we have sought the proper length of time period out from extensive tests.

For the entry detection, two states are defined based on the observed RSS difference. When the RSS difference is above zero, it is in 'inside' state, and when the difference is below zero, it is in 'outside' state. Basically the entry/exit detector infers the entry or exit (of a student) based on whether the state transition between two states (inside and outside) occurs or not. But the state transition near the door can frequently occur due to unstable RSS fluctuations. Thus we introduce a ***state holding threshold,*** which means the minimum holding time for determining either of the two states to avoid the wrong state decision. That is, the state transition only occurs if the holding time for new state exceeds the state holding threshold. We set the state holding threshold to 4 seconds from comprehensive experiments. Note that the RSS difference can be only observed around the door due to the limitation of the communication range of two beacons, and the observation time is near 8~10 seconds before and after passing the door, with moderate walking speed. Thus, 4 seconds for state holding threshold is proper because it can cover the half of the state sojourn time. Also, note that low pass filter is applied to the RSS difference to smooth the pattern.

Lastly, the attendance is only checked true when both the inside detector and the entry/exit detector indicate that the student is inside the classroom, and the attendance is checked false at least one of them indicates that the student is outside the classroom. Note that the app will be triggered earlier than the class hours since we may have to cover the case of early arrival of the student. The class hours can be recorded by the student, or obtained from the university information infrastructure.

The walking mode estimator is an auxiliary component of the system. If the smartphone continuously scans BLE signals, its battery will be drained soon. Thus, the smartphone app for checking the attendance will be activated periodically (say, every 5 minutes) during the student's class hours. Furthermore, the walking mode estimator leverages a pedestrian dead reckoning (PDR) mechanism that infers a student's walking mode based on (i) the detection of steps and (ii) the estimation of the heading direction; this component is also intermittently running only when the attendance checking app is activated. If the student has not moved, the app does not need to perform the BLE scanning and goes to the sleeping state for energy saving purposes. This sleeping process is based on an assumption that students do not generally move during the class.

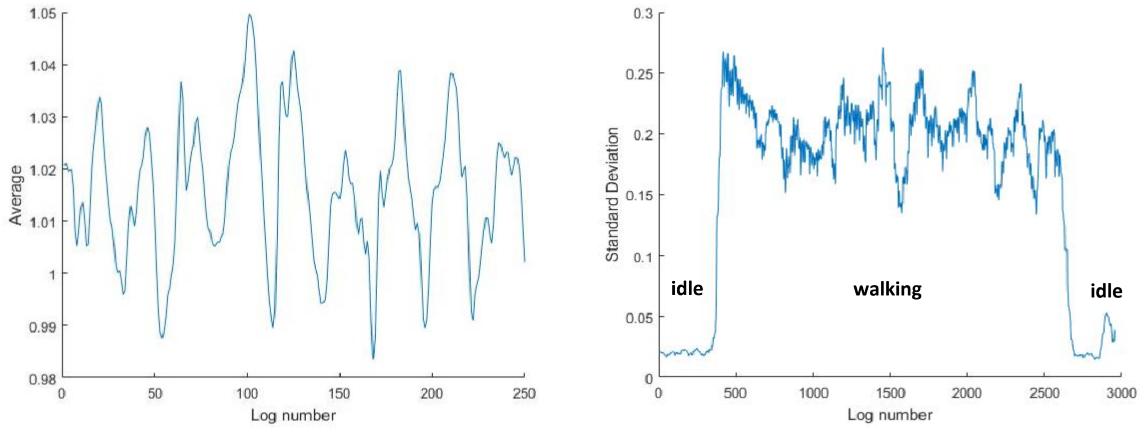

Figure 9. Repetitive pattern of acceleration magnitudes is plotted while a student is walking, and the change of standard deviations is also shown during idle and walking modes.

To detect the walking mode, we adopt the step detection module as proposed in ZEE[33]. The left one of Fig. 9 plots the repetitive pattern of the magnitudes of the smartphone accelerometer while walking. The right figure shows the patterns of standard deviations of the magnitude of the acceleration in idle and walking modes. ZEE uses a combination of both the repetitive pattern detection and the monitoring the standard deviations to detect the walking mode. Note that the unit of y-axis is normalized by the acceleration of gravity.

Implementation

We implemented an Android app to evaluate the proposed scheme. The app currently runs all the components; walking motion estimator, BLE scanning, inside detector, entry/exit detector, and attendance checking component. As future work, a back-end server will be implemented to check the attendance of all students in a centralized fashion. All the components related to the attendance checking algorithm will be moved to the back-end server, except the BLE scanning and walking motion estimator.

Evaluation

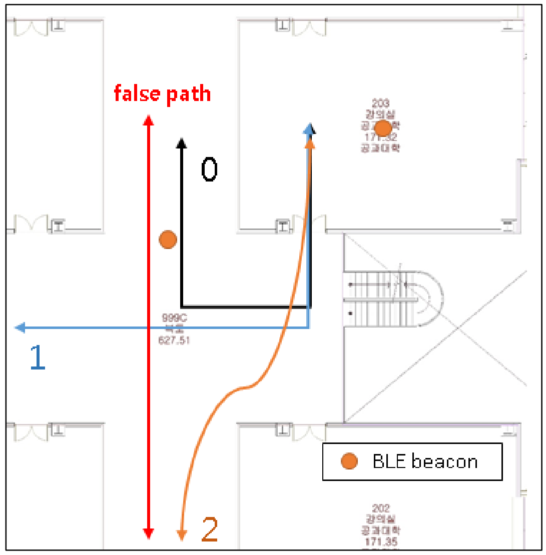

Figure 10. Three paths (0, 1, 2) to the classroom and one wrong path (drawn red) to be tested are shown.

To evaluate the system, we tested the app for three paths to the classroom and one wrong path along the corridor around the classroom. For the three (right) paths, a test student carrying a smartphone in her hand moves along the paths as shown in Fig. 10, and then stays in the classroom for 15~20 seconds. The student does not enter the classroom in case of the wrong path. Note that the same paths are also tested in the opposite direction (from the classroom to the corridor).

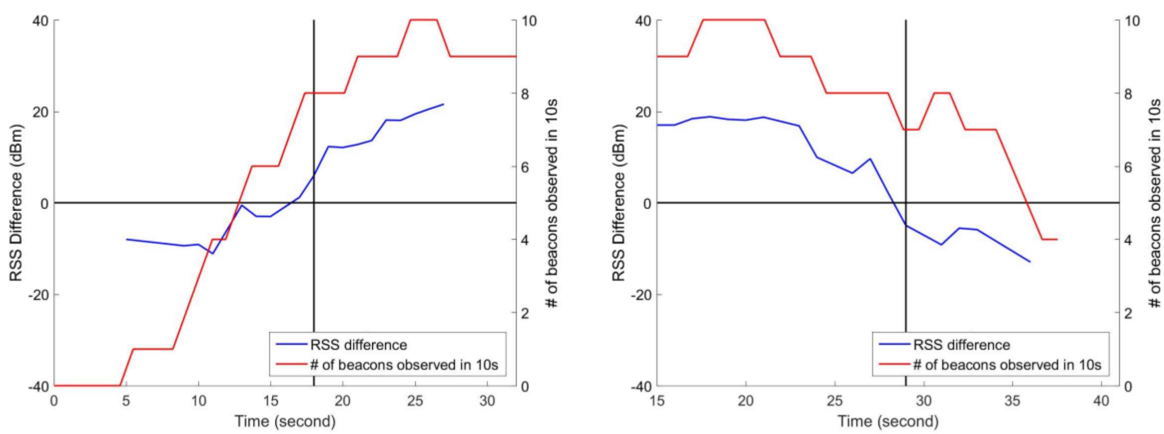

Figure 11. One example of the change of RSS differences and the number of beacons observed at 10 second intervals as the student enters or exits the classroom

Overall, the attendance is successfully checked true as the student enters the classroom in all the three paths, and checked false as she goes out of the classroom. As an example, the left one of Fig. 11 plots the change of RSS differences and the number of beacons observed in 10 seconds when entering the classroom along path 1, and the right one plots the measured values when exiting the classroom along path 1 (in the reverse direction). Again, the black vertical line means the moment at which the experimenter passes the door, and the black horizontal line in the center means the algorithm threshold for both the inside detector and the entry/exit detector.

The comprehensive experiments reveal that (i) the inside detector detects a student's moving into the classroom earlier than the actual entry moment, and (ii) the inside detector detects a student's moving out of the classroom later than the actual exit moment. This behavior can be explained by two things: (i) conservative (i.e., high) Tx power of the inside beacon and (ii) the inside detector's low threshold considering the worst case (i.e., a student at NLOS positions). As shown in the earlier measurements, we adopt the sufficiently low threshold for the rate of received beacons, and the sufficiently high communication range of the inside beacon to cover NLOS positions of students to prevent false negatives. Note that the time difference of the inside detector's detection (of the student's moving) is 6~7 seconds from the door passing moment from the comprehensive tests. Note that the detection delay of the entry/exit detector is shorter and its detection is more accurate than the inside detector. However, we still need to use the inside detector for many cases such as a student's arriving at the classroom much earlier.

When the student is entering the classroom, the inside detector detects the entry earlier than the actual passing time, but the attendance can be checked true only when both the inside detector and the entry/exit detector conclude that she is in the classroom. Thus, the attendance checking time usually coincides with the entry/exit detector's detection time, which is accurate. The system's behavior in the student's exiting case is similar to the above entry case. The attendance checking time follows the entry/exit detector's detection time because the attendance can be checked false when either of the two detectors in our scheme deems that the student is outside the classroom. The attendance checking times in all the cases are within 5 seconds from the door passing moment, in spite of the state holding threshold of the entry/exit detector.

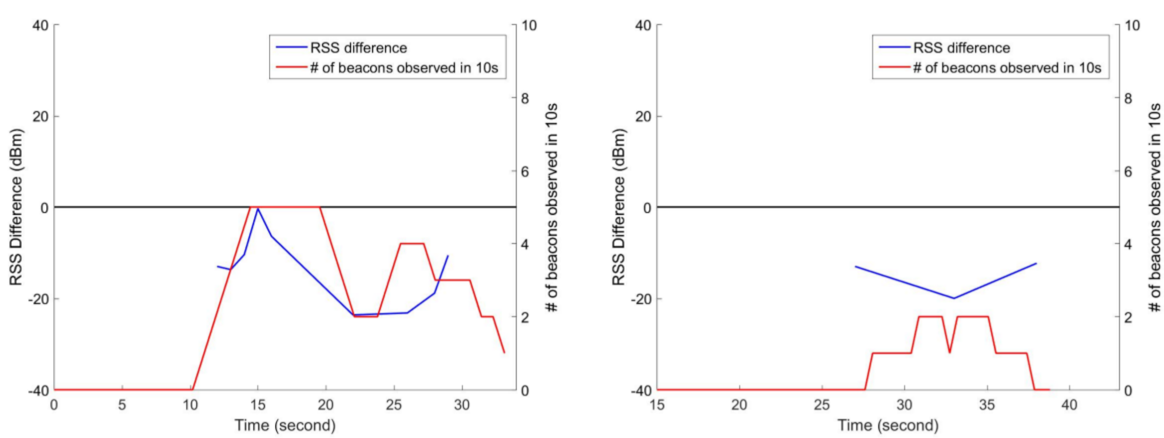

Figure 12. The RSSs and the numbers of received beacons are plotted when the test student walks over the wrong path in upward and downward directions (on the map), which are shown on the left and right, respectively.

Fig. 12 shows the measurement data of the smartphone along the wrong path. In case of the upward direction, the inside detector concludes that the student is in inside state from 14 seconds to 20 seconds, because the number of observed beacons is greater than or equal to the threshold (the threshold is 5). As shown in Fig. 10, if the student moves in the upward direction, her smartphone can be located in a LOS position to the inside beacon when she gets close to the classroom. Hence, the inside detector reports false positive cases at some points. However, due to the entry/exit detector, the attendance is checked false. It turns out that our system can effectively distinguish the false positive cases by leveraging the entry/exit detector.

Related Work

In recent years, a range-based localization scheme[34] that finds out the user location by calculating the distance to the reference node has been intensively studied and proposed. Among range-based localization schemes, one of most popular approaches is an RSS-based one that uses the fact that the received signal strength is decreased as the distance increases. There have been many studies that belong to the RSS-based approach with a diverse set of wireless technologies including WiFi[17,22,23], WSN (Wireless Sensor Network)[26,28], Bluetooth[15], acoustic signal[25,27,29,30] and etc[12,19,20,24].

Another approach uses the time information to calculate the distance. This kind of schemes rely on time related information such as Time-of-Departure (ToD), Time-of-Arrival (ToA) to estimate the distance. For instance, the Time-of-Flight (ToF) approach captures the propagation time of a wireless signal between a client and an AP to estimate the distance between two entities[14,16,18,21].

In this paper, we propose a geofencing scheme that is somewhat different from the range-based localization. Whereas range-based localization schemes try to estimate the location of the user accurately, geofencing tries to figure out whether a user is within an area of interest or not rather than calculating the exact location the user[10,11,13].

Discussions

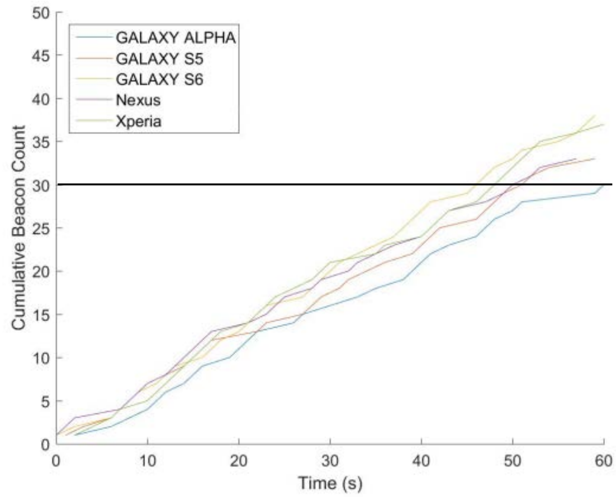

Figure 13. Cumulative numbers of observed beacon frames for one minute are measured across different devices

1. Device diversity: There is a well-known issue called "device diversity," which can be critical in measuring radio frequency signals[35]. The "device diversity problem" refers to the phenomenon that the RSS and beacon detection can deviate significantly as different devices are used in measurements. This problem comes from the different antenna type and communication module of devices including smartphones, and it might make instability in the performance of the inside detector. Fig. 13 shows the number of observed beacon frames for one minute from different devices. The black horizontal line means the threshold of inside detector (detection rate 0.5), and 'Galaxy Alpha' model only fails to satisfy the threshold. Setting different thresholds for difference devices might be a solution.

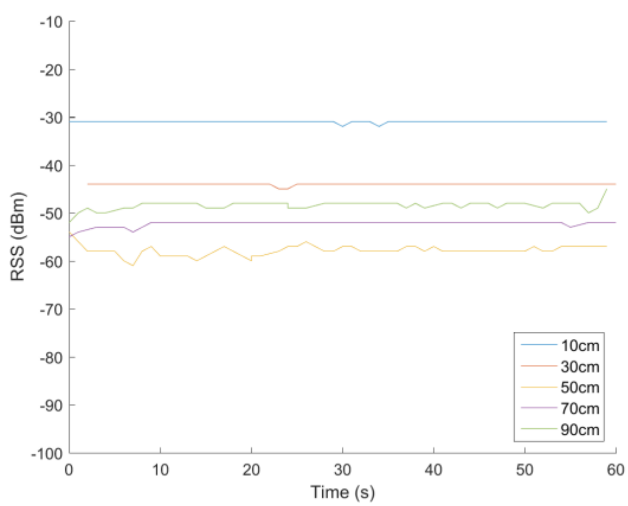

Figure 14. The RSS values between two smartphones are plotted for different distance.

2. Preventing a student from carrying multiple devices (attendance cheating): Our attendance checking system fully depends on the BLE scanning of smartphone. A student can thus abuse our system if she carries not only her smartphone but also that of other student. To prevent this, a simple idea can be applied. A smartphone can send its own BLE beacon frame like the BLE beacon nodes, so other smartphones can measure the RSS value from that smartphone nearby. It means that we can approximately measure the distance between the smartphones by observing their RSS values. Of course the RSS fluctuation can occur in this case as well, but the distance between the smartphones carried by the same student is very short. Hence the RSS values tend to be stable and high. Fig. 14 depicts the RSS values between two smartphones located less than 1m distance. The RSS values are quite higher than those of the previous measurements, and thus the attendance cheating can be detected. We plan to substantiate this idea as future work.

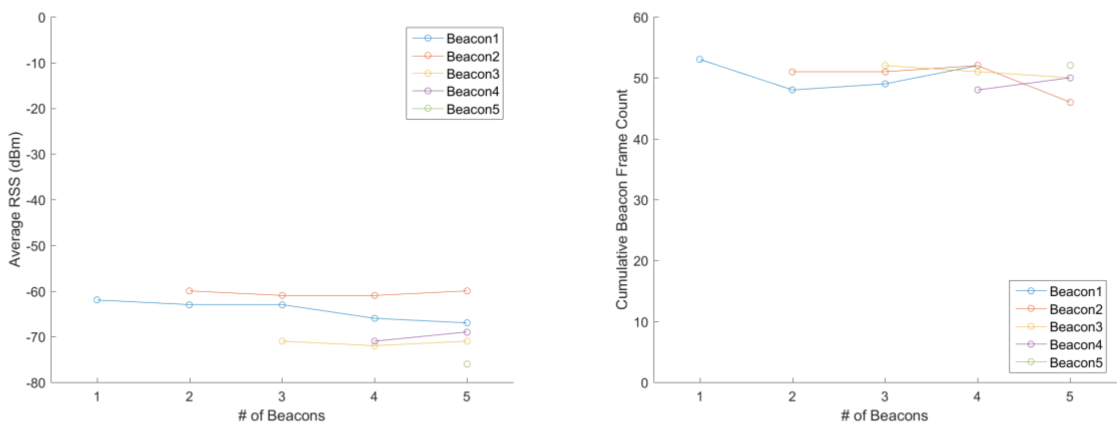

Figure 15. The RSSs and the numbers of observed beacon frames when multiple beacons (i.e., smartphone) are located at the same position.

3. BLE signal conflict: Fig. 15 shows the change of the average RSSs and the numbers of observed beacon frames for one minute as the number of BLE beacons increases. We deploy five beacons at the same position, and each beacon is individually turned on periodically for one minute. BLE employs frequency hopping as a base communication scheme to avoid the interference. The result also shows no significant signal conflict between the beacons. Thus our system can be deployed without too much interference among beacons. Note that BLE beacon frames use non-overlapping frequency bands with WiFi frames. Also each classroom can easily be distinguished by the MAC address of each beacon which has the unique value.

4. Compatibility: Our system only relies on the BLE scanning functionality of the smartphone, and the algorithmic computations can be carried out by a back-end server. Thus the system can easily be installed into various smart devices on different OS platforms like iOS, Tizen, Windows mobile only if the devices support the APIs for the BLE scanning.

Conclusion & Future Work

In this paper, we proposed a smartphone software tool for checking the attendance of students in an automatic fashion. We seek to design a BLE-based "geofencing" system that figures out whether a student with her smartphone is inside or outside of a classroom. The comprehensive measurements of BLE show that the observation of the beacon frames from an inside beacon is not sufficient. The key idea of this paper is to introducing an entry/exit detector based on the difference between her smartphone's RSS values of two BLE beacons; one beacon is inside the classroom and the other is outside the classroom. We implement an Android app to evaluate our system, which achieves good performance in campus building environments. As future work, we first carry out experiments with multiple entry/exit detectors, and seek to enhance the energy efficiency of the proposed scheme. We then plan to generalize the solution for various sizes of classrooms and various smart devices.

Acknowledgements

The SNU-Samsung smart campus research center at Seoul National University provides research facilities for this study. This work was supported by the National Research Foundation of Korea (NRF) Grant (No. 2015R1A5A7037372) funded by the Korean Government (MSIP). This work was also supported by Institute for Information & communications Technology Promotion (IITP) grant funded by the Korea government (MSIP) (No. B0717-16-0034, Versatile Network System Architecture for Multi-dimensional Diversity).

References

[1] Bluetooth SIG, What is Bluetooth technology?, https://www.bluetooth.com/what-is-bluetooth-technology/bluetooth-technology-basics/low-energy

[2] Bahl, Paramvir, and Venkata N. Padmanabhan. "RADAR: An in-building RF-based user location and tracking system." INFOCOM 2000. Nineteenth Annual Joint Conference of the IEEE Computer and Communications Societies. Proceedings. IEEE. Vol. 2. Ieee, 2000.

[3] Insight, http://www.beestar.eu

[4] Anyplace, http://anyplace.cs.ucy.ac.cy

[5] Locatible, http://locatible.com

[6] MazeMap, http://www.mazemap.com

[7] Munson, Jonathan P., and Vineet K. Gupta. "Location-based notification as a general-purpose service." Proceedings of the 2nd international workshop on Mobile commerce. ACM, 2002.

[8] LSI Healthcare, http://lsi-healthcare.com/location-aware-mobile-apps-for-healthcare

[9] Cisco, The Cisco Location-Aware Healthcare Solution, http://www.cisco.com/c/dam/en_us/solutions/industries/docs/healthcare/CLA_HealthcareSolution.pdf

[10] Ahmed, Nasimuddim, et al. "SmartEvacTrak: a people counting and coarse-level localization solution for efficient evacuation of large buildings." Pervasive Computing and Communication Workshops (PerCom Workshops), 2015 IEEE International Conference on. IEEE, 2015.

[11] Aparicio, Sofıa, et al. "A fusion method based on Bluetooth and WLAN technologies for indoor location." Multisensor Fusion and Integration for Intelligent Systems, 2008. MFI 2008. IEEE International Conference on. IEEE, 2008.

[12] Tarrío, Paula, et al. "An energy-efficient strategy for combined RSS-PDR indoor localization." Pervasive Computing and Communications Workshops (PERCOM Workshops), 2011 IEEE International Conference on. IEEE, 2011.

[13] Biehl, Jacob T., et al. "Loco: a ready-to-deploy framework for efficient room localization using wi-fi." Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing. ACM, 2014.

[14] Xiong, Jie, and Kyle Jamieson. "ArrayTrack: A Fine-Grained Indoor Location System." NSDI. 2013.

[15] Jianyong, Zhu, et al. "RSSI based Bluetooth low energy indoor positioning." Indoor Positioning and Indoor Navigation (IPIN), 2014 International Conference on. IEEE, 2014.

[16] Sen, Souvik, et al. "Bringing CUPID Indoor Positioning System to Practice." Proceedings of the 24th International Conference on World Wide Web. International World Wide Web Conferences Steering Committee, 2015.

[17] Sen, Souvik, et al. "Avoiding multipath to revive inbuilding wifi localization." Proceeding of the 11th annual international conference on Mobile systems, applications, and services. ACM, 2013.

[18] Mariakakis, Alex T., et al. "Sail: Single access point-based indoor localization." Proceedings of the 12th annual international conference on Mobile systems, applications, and services. ACM, 2014.

[19] Uddin, Muslem, and Tamer Nadeem. "SpyLoc: a light weight localization system for smartphones." Sensing, Communication, and Networking (SECON), 2014 Eleventh Annual IEEE International Conference on. IEEE, 2014.

[20] Yang, Lei, et al. "Tagoram: Real-time tracking of mobile RFID tags to high precision using COTS devices." Proceedings of the 20th annual international conference on Mobile computing and networking. ACM, 2014.

[21] Xiong, Jie, Karthikeyan Sundaresan, and Kyle Jamieson. "ToneTrack: Leveraging frequency-agile radios for time-based indoor wireless localization." Proceedings of the 21st Annual International Conference on Mobile Computing and Networking. ACM, 2015.

[22] Wu, Kaishun, et al. "Fila: Fine-grained indoor localization." INFOCOM, 2012 Proceedings IEEE. IEEE, 2012.

[23] Zhang, Dian, et al. "On distinguishing the multiple radio paths in rss-based ranging." INFOCOM, 2012 Proceedings IEEE. IEEE, 2012.

[24] Zhao, Yu, et al. "FREDI: Robust RSS-based ranging with multipath effect and radio interference." INFOCOM, 2013 Proceedings IEEE. IEEE, 2013.

[25] Liu, Kaikai, et al. "Towards accurate acoustic localization on a smartphone." INFOCOM, 2013 Proceedings IEEE. IEEE, 2013.

[26] Xiao, Fu, et al. "Noise-tolerant localization from incomplete range measurements for wireless sensor networks." Computer Communications (INFOCOM), 2015 IEEE Conference on. IEEE, 2015.

[27] Peng, Chunyi, et al. "Beepbeep: a high accuracy acoustic ranging system using cots mobile devices." Proceedings of the 5th international conference on Embedded networked sensor systems. ACM, 2007.

[28] Sun, Zheng, et al. "Cortina: Collaborative context-aware indoor positioning employing RSS and RToF techniques." Pervasive Computing and Communications Workshops (PERCOM Workshops), 2011 IEEE International Conference on. IEEE, 2011.

[29] Lazik, Patrick, and Anthony Rowe. "Indoor pseudo-ranging of mobile devices using ultrasonic chirps." Proceedings of the 10th ACM Conference on Embedded Network Sensor Systems. ACM, 2012.

[30] Lazik, Patrick, et al. "ALPS: A bluetooth and ultrasound platform for mapping and localization." Proceedings of the 13th ACM Conference on Embedded Networked Sensor Systems. ACM, 2015.

[31] Pathanawongthum, Nichapat, and Panarat Cherntanomwong. "Empirical evaluation of RFID-based indoor localization with human body effect." Communications, 2009. APCC 2009. 15th Asia-Pacific Conference on. IEEE, 2009.

[32] Eleryan, Ahmed, Mohamed Elsabagh, and Moustafa Youssef. "Synthetic generation of radio maps for device-free passive localization." Global Telecommunications Conference (GLOBECOM 2011), 2011 IEEE. IEEE, 2011.

[33] Rai, Anshul, et al. "Zee: zero-effort crowdsourcing for indoor localization." Proceedings of the 18th annual international conference on Mobile computing and networking. ACM, 2012.

[34] Cheng, Long, et al. "A survey of localization in wireless sensor network." International Journal of Distributed Sensor Networks 2012 (2012).

[35] Park, Jun-geun, et al. "Implications of device diversity for organic localization." INFOCOM, 2011 Proceedings IEEE. IEEE, 2011.