Building a Practical Wi-Fi-Based Indoor Navigation System

This article presents the seven-step process involved in building a practical Wi-Fi-based indoor navigation system, which was implemented at the COEX complex in Seoul, Korea, in 2010. More than 200,000 users downloaded the system in its first year of use.

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As car navigation systems have become more ubiquitous, researchers have recognized the potential for indoor navigation systems to help pedestrians find their way in complicated indoor areas such as airport terminals, subways, shopping malls, and exhibition and convention centers. In addition, the recent proliferation of Wi-Fi-equipped smartphones and the rapid expansion of Wi-Fi zones have moved this idea from wishful thinking to near reality.

In October 2010, a Wi-Fi-based indoor navigation system for the COEX complex (a landmark area in Seoul, Korea) was released by our team at the Korea Advance Institute of Science and Technology to smartphone users via the myCoex application. The COEX area comprises Asia's largest underground shopping mall area, three five-star hotels, one 55-story and one 41-story premier office tower, a large department store, a subway station, a city airport terminal, and more.

Although we proved that it's possible to build a practical Wi-Fi-based indoor localization system, developing such a system for a large indoor area wasn't an easy task. Here, we review the long and tedious steps required.

The COEX Complex

Figure 1 provides a schematic view of the COEX complex. The buildings, towers, and stores in the COEX area are mostly interconnected via the COEX underground shopping mall area in the B1 level. The total length of the paths is more than 10 km, and the total size of the COEX underground shopping mall area amounts to more than 450,000 m^2 (comparable to 70 football stadiums). Large parking areas, located on the B2, B3, and B4 levels, can accommodate approximately 3,000 cars. More than 200 exhibitions and 2,000 conferences are held at the COEX every year.

Although previous work confirmed the feasibility and potential of Wi-Fi-based localization techniques,[1] customers and vendors have been reluctant to apply these techniques when developing location-based service (LBS) applications that require high localization accuracy, particularly in large indoor spaces. Most work failed to provide convincing evidence to customers and vendors, because the experiments were conducted in relatively small and confined indoor areas—not larger spaces, such as COEX.

Seven-Step Development Process

To address this issue, we decided to test existing Wi-Fi-based indoor localization techniques and integrate them to build the COEX indoor

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navigation system.[1–5] However, the available techniques weren't sufficient. Along with Wi-Fi signal-collection support tools, we developed a signal and two location filters, and integrated them with the COEX indoor navigation system to make the system more reliable and stable. All of this comprised a seven-step process, which we outline here (see Figure 2).

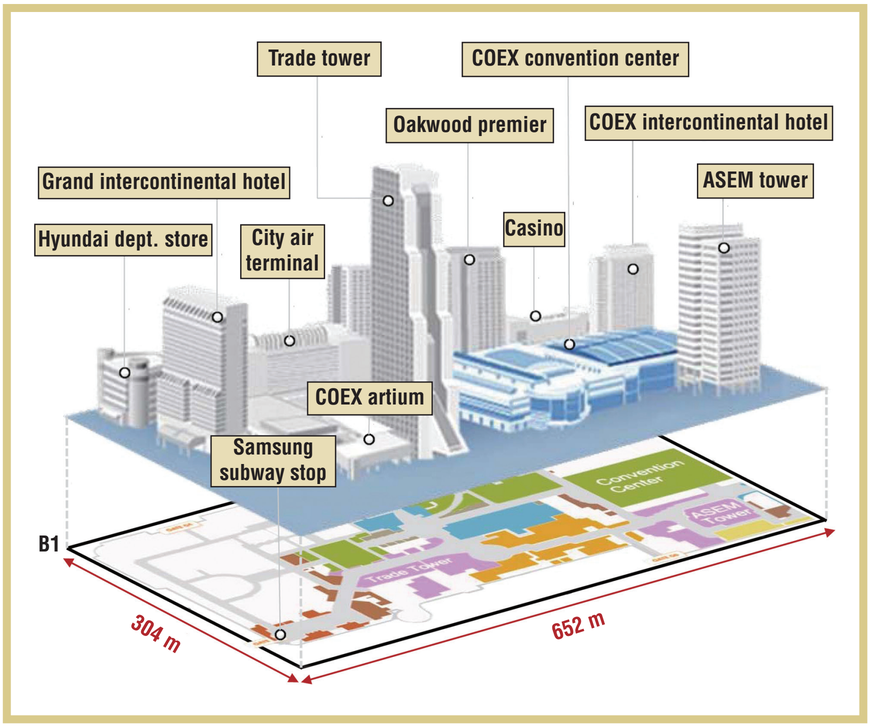

Figure 1. A schematic view of the buildings in the COEX area. All of the buildings in the block are interconnected via underground paths in the B1 level.

Access Point Analysis

Analyzing the Wi-Fi or access point (AP) environment in a target indoor area is the first step in building a Wi-Fi-based indoor navigation system. This step should be first because the decision to install more APs to further enhance the localization accuracy should be made based on the results of this analysis.

Identifying the areas with only weak Wi-Fi signals is the primary goal of this step. Thus, it's enough to roughly divide the target area into many small subareas, and count the number of accessible Wi-Fi signals and signal strengths at the subareas. If necessary, additional APs should be installed in the subareas lacking strong AP signals.

In general, a very large indoor area, such as COEX, is a combination of distinctively different places, where many AP signals are available, no AP signal is available, or the captured Wi-Fi signals are too weak for localization. Among the hundreds of subareas in the COEX area, approximately 10 were poor-AP areas, with only weak Wi-Fi signals available, so we installed about 200 additional APs in those areas to improve the localization accuracy.

Design Goals Set Up

We established the design goals for the COEX indoor navigation system under the constraint of using the deployed APs only for communication purposes. To set practical design goals, we implemented a prototype navigation system and conducted preliminary experiments to collect user experiences dozens of times at a part of the B1 floor of COEX. The preliminary experiments revealed that the accuracy of the localization could fluctuate from 3 to 15 meters, depending mainly on the density and distribution of APs.

In addition, users preferred to have their positions updated on the map in regular intervals. Based on these initial experiments and observations, we set 5–6 meters as the allowable average error distance in the error-sensitive areas, and 6–8 meters as the overall average error distance to be achieved by the system at COEX. Also, based on user experiences and the minimum Wi-Fi signal scanning time (MST), we set the average response time of localization to MST + 1 seconds.

Lastly, we aimed for the overall size of the system not to exceed 4–5 megabytes, including the Wi-Fi fingerprint database, so the system could be easily downloaded and installed on a user's smartphone.

Indoor Map Drawing

The third step is to prepare an indoor map that displays the user's path and position. The indoor map is used not only for directing users but also for marking the locations to collect the Wi-Fi fingerprints. Although drawing an indoor map is neither difficult nor complicated, the map should be carefully prepared to make the indoor navigation system more precise and convenient. Using a manually drawn indoor map is better, because such a map is much cleaner and neater than one generated from a CAD map using a tool. Once the map is ready, one corner of the map is determined as the original point to specify a position on the map in coordinates. Along with the decision on the original point, the x- and y-axes are also decided. These initial coordinates should then be converted into standard coordinates to integrate the indoor map with outdoor maps.

On the map, a user's location is displayed on the edges (or links) connecting the nodes (or waypoints) of a network. All the paths are represented on the map using a network connecting the waypoints. The waypoints are marked at the ends of a path, at

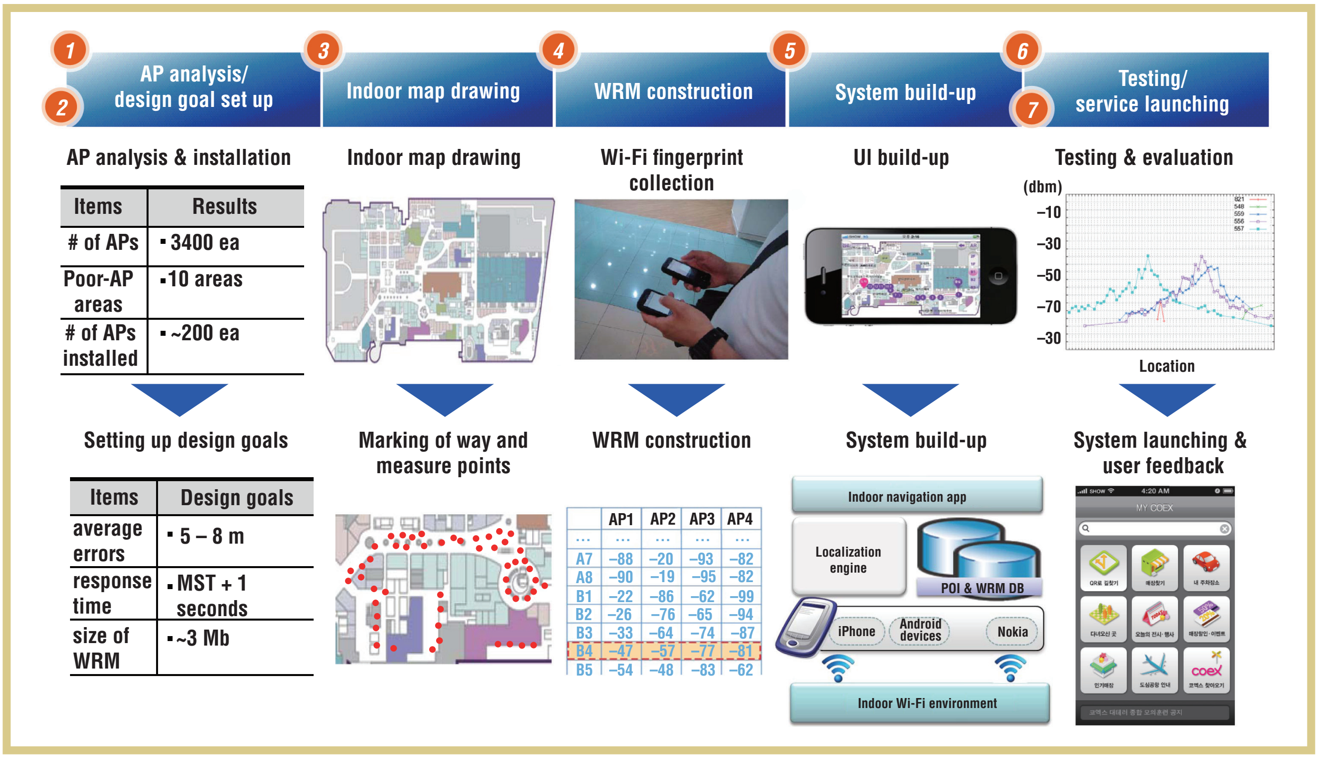

Figure 2. The seven steps in building an indoor navigation system for a large indoor area.

corners, and at intersections. Usually, two waypoints are enough to represent a straight line, but when a path is rather long or bent, multiple waypoints might need to be used so that the path can be represented by connecting the waypoints.

Once the network is prepared, the measure points are marked to collect the Wi-Fi fingerprints on or alongside the links of the network. The tool in Figure 3a shows the task of marking the measure points. In the tool, a circle represents a waypoint, and an arrow connecting the circles represents a link. A line can be drawn by marking each end of the line with blue cross marks as reference points. The planners must decide on and mark the reference points in advance. Once both ends of a line are decided, the measure points on the line are automatically generated in the same interval by the tool.

When a corridor was too wide to be covered by a single measurement line, multiple lines were drawn along the way link. The number of lines to be drawn was determined by a simple function, $\lceil w/i \rceil$, where w is the width of a corridor and i is a predefined interval between two adjacent measure points—3 meters in our case.

Wi-Fi Radio Map Construction

After marking the measure points on the map, the next step requires collecting precise Wi-Fi fingerprints at each marked measure point, which is critical for accurate localization.[6] The Wi-Fi fingerprints should be densely collected for an accurate localization, and at least 20–30 Wi-Fi fingerprints should be collected at each point for reliability. Consequently, the Wi-Fi fingerprint collecting activity in a large-scale indoor space can be difficult and time-consuming. In COEX, dozens of collectors performed the collecting activity in parallel, after dividing the entire area into several subareas—each of which was assigned to a particular collection team.

We developed a radio map interpolation technique to reduce the efforts of collecting Wi-Fi fingerprints by artificially generating Wi-Fi fingerprints using the relatively smaller number of manually collected Wi-Fi fingerprints.[5] However, the results of applying the interpolation technique could hardly outperform the accuracy achieved on the manually collected Wi-Fi fingerprints. With COEX, the interpolation technique was applied only for the parking areas.

For data collection, the collectors download the maps marked with the reference points to their smartphones (Figure 3b), choose and locate the marked reference points, and then start collecting the Wi-Fi fingerprints along the lines connecting the reference points. They use their smartphones' Wi-Fi fingerprint-collecting tool for this purpose (Figure 3c). The tool supports the collectors to check if the location where the collection has started is the correct location by providing information on every reference point. The interval between two adjacent collection points is set to a predetermined

Figure 3. Waypoint marking: (a) the tool to mark the measure points and waypoints on a PC, (b) a map downloaded to a smartphone marked with the reference points, and (c) the tool to collect Wi-Fi fingerprints on a smartphone.

interval, 3 meters in our case, to map them to their corresponding measure points afterwards. In the case of COEX, the collector could ensure the interval relatively easily because the floors were tiled with 40 × 40 cm square tiles. Without the tiles, we might need to use a distance measurement tool to ensure the interval.

The Wi-Fi fingerprint collecting activity was performed by 15 collectors for two weeks. We organized seven teams: six teams with two members in each team for collection, and one team with three staff members for supporting the collection activities of the six teams. The Wi-Fi fingerprints were collected at about 10,000 measure points, and 20 Wi-Fi fingerprints were collected at each point, resulting in a data collection of around 200,000 total Wi-Fi fingerprints. Also, the 20 Wi-Fi fingerprints at each point were merged into an average Wi-Fi fingerprint, so approximately 10,000 average Wi-Fi fingerprints were collected into the Wi-Fi radio map (WRM—available for download at https://kailos.io/wrm/seoul/coex).

We used a Samsung Galaxy S1 for the collection. In the Galaxy S1, the Wi-Fi-antenna is on the bottom left of the phone, so we instructed collectors not to hold the bottom of the phone and not to move or change the height of the phone while collecting 20 fingerprints. Although the collector's body could cause the attenuation of signal strengths, we asked the collectors to hold the phone in front of their chests facing one direction. We confirmed that the accuracy was not, or was only slightly, influenced by the body and direction in a very crowded area such as COEX.

System Build-Up

After preparing the WRM, indoor map, and way network, we installed a localization engine on the WRM and the path-finding routine on the indoor map. Then, we installed the navigation applications on top of the localization engine and path-finding routine.

The localization engine installed on the WRM is the core component of the indoor navigation system. Along with the WRM, the performance of the engine is critical for a more accurate localization. Accordingly, various techniques and filters should be integrated together with the localization engine.

We adopted the k-weighted nearest neighbors (kWNN, $k = 3$) for our localization engine,[7] because it was slightly more accurate than other methods at COEX,[8] and it was flexible for fine-tuning and further enhancing the engine's accuracy. The kWNN simply outputs the weighed centroid of the top k locations, with the weights determined by the distance between the captured fingerprint and each nearest neighbor. However, the accuracy level required for the practical use of the system couldn't be achieved solely with the localization engine.

Thus, we developed a *signal filter*, an *adaptive Kalman filter*, and a *delay filter*, and integrated them with the localization engine to further improve accuracy. The localization engine deals with only a single Wi-Fi fingerprint at a time, whereas the filters use the sequences of the consecutively scanned Wi-Fi fingerprints or locations (that is, historic data). Given that Wi-Fi fingerprints can be scanned every two or three seconds for indoor navigation, the approach taken by the filters is reasonable.

Strong Wi-Fi signals are sometimes missed in a captured fingerprint because of limited scanning time. The signal filter imputes the Wi-Fi fingerprint captured for localization using

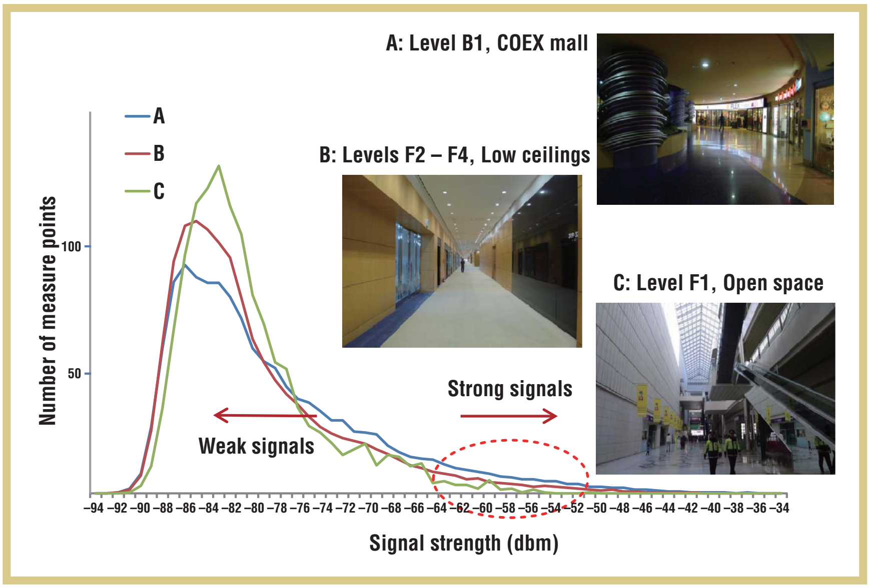

Figure 4. Distributions of the Wi-Fi signal strengths observed in areas A, B, and C of COEX. Localization accuracy depends on the density of strong Wi-Fi signals. Strong Wi-Fi signals were detected more frequently in area A than in areas B and C.

the Wi-Fi fingerprints in WRM.[9] That is, if a particular AP signal, which appears in most of the fingerprints in the WRM on a recent path, isn't included in a scanned Wi-Fi fingerprint, the AP signal is imputed to the scanned Wi-Fi fingerprint. The signal filter was placed between the Wi-Fi signal scanning module and the localization engine.

Unlike the signal filter, the other two filters were placed between the localization engine and the map-matching for smoothing any user movement. The adaptive Kalman filter, which is a variant of the extended Kalman filter (EKF),[10] switches its mode back and forth from the EKF to the particle filter.[11] On a straight line, the EKF is activated, whereas when a user approaches corners or intersections, the particle filter is activated instead.

We also integrated a delay filter with the localization engine. It can delay or skip the display of the estimated location if the estimated location deviates too far from the previously estimated locations. In a normal situation, the delay filter displays the middle point of the two locations as its estimated location.

The path-finding module finds an optimal path using the users' current location and the destination. To facilitate users' designation of the destinations, the navigation system has all points of interest (POIs) registered in advance so that users can choose their destinations out of the registered POIs. In general, the registered POIs include stores, offices, places, and major crosspoints. Our path-finding routine is based on the Dijkstra's shortest-path-finding algorithm. The path-finding routine should not merely find the shortest path on a way network. Rather, it should find a path that pedestrians routinely choose to get to their destinations. Because there could be many different paths depending on the selections of stairs, escalators, and elevators when a user changes floors, the path-finding routine must reflect the typical moving patterns of the pedestrians in the target area.

System Testing

For the test, we captured the Wi-Fi signals on a smartphone every one to three seconds, estimated its location using the localization engine, and then displayed the estimated locations on the way network after the map matching. Note that the minimum Wi-Fi scanning time (MST) varies from one to three seconds, depending on the type of scanned Wi-Fi signals: 2.4 GHz, 5 GHz, or both of them. But the frequent scanning of Wi-Fi signals could drain the battery more quickly. When the scanning was performed every second without localization in a Galaxy S1, the battery was drained in 12 hours, whereas it lasted for 16 hours when scanning was performed every three seconds. However, when the localization was made after each scanning, the batteries were drained in 3.8 hours in both cases.

Among the filters, only the delay filter was used to control outliers at the beginning. The results were a mixture of good and bad areas in terms of accuracy. In some areas, the locations were displayed in a stable manner, whereas in some others, the results were unstable. In particular, when we approached escalators to change floors, the wrong floor was often displayed even before we got on the escalators.

We collected test data at around 1,000 predesignated points to get practical results. To get more meaningful results, we divided the COEX area into three subareas for the measurement—areas A, B, and C. Area A comprised the complex B1 level; area B comprised levels F2, F3, and F4, which have a relatively low ceiling area; and area C comprised the open space in level F1. Several long escalators in the open space connect areas B and C. We excluded the parking areas in levels B2–B4 from the measurement.

On average, 28.6 APs were detected in each Wi-Fi fingerprint in area A, 35.7 APs in area B, and 61.1 APs in area C. The Wi-Fi fingerprints collected at area A were found to have the fewest AP signals, whereas strong Wi-Fi signals were detected most frequently in area A. On the other hand, strong Wi-Fi signals were least frequently detected in the Wi-Fi fingerprints collected in area C, although they had the most APs. Figure 4 shows the distribution of the AP signal strengths observed in each area. We obtained the average error distances

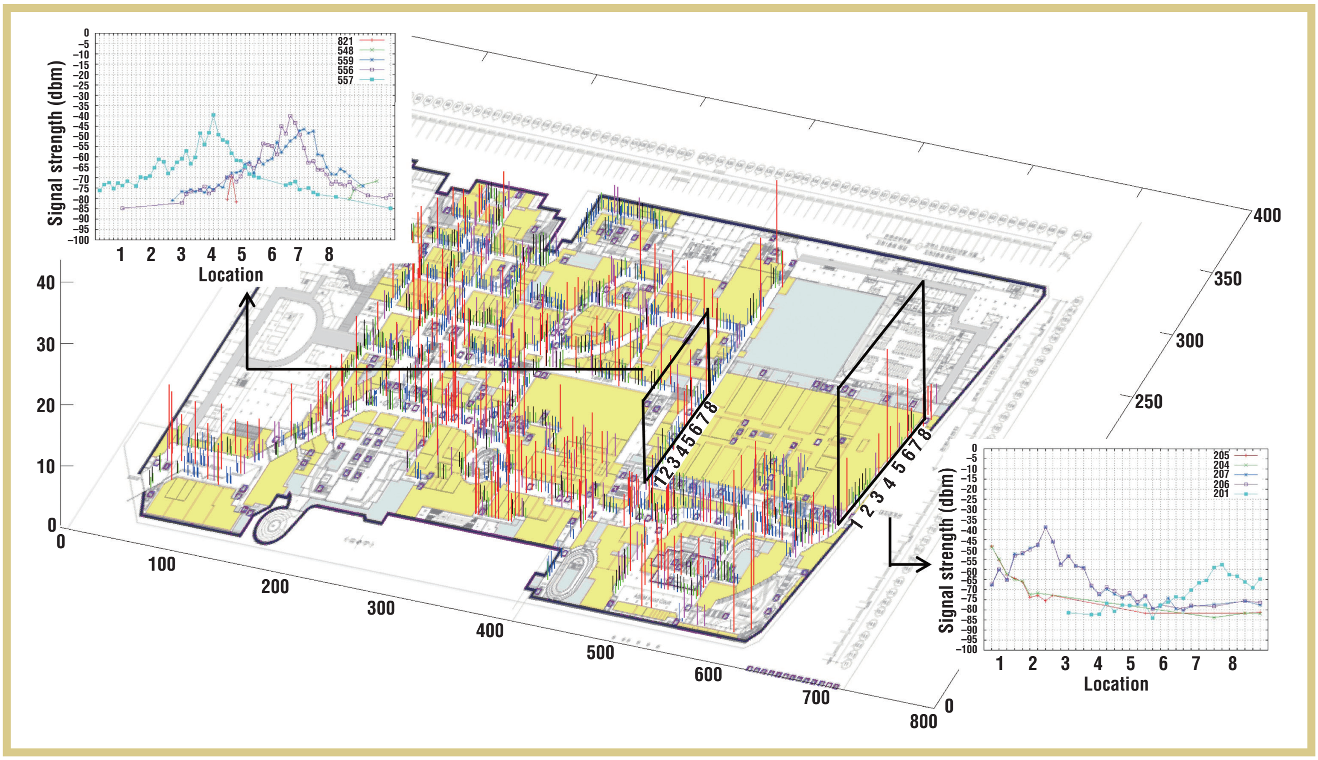

Figure 5. Measured accuracy and Wi-Fi signal distributions excerpted from the box areas in the B1 level of COEX. The accuracy of the areas with only weak Wi-Fi signals was always worse than that of the areas with strong Wi-Fi signals. Black, blue, violet, and red bars represent 3-, 6-, 9-, and more than 12-meter error distances, respectively.

of 6.0 meters at area A, 5.9 meters at area B, and 7.1 meters at area C. Considering that no special APs were installed to support localization, the results aren't so bad. The floor-level accuracies obtained at areas A, B, and C were 99.6, 96.2, and 90.6 percent, respectively.

The accuracy differences in each area indicate that the strength of AP signals in Wi-Fi fingerprints is more important to accuracy than the number of AP signals. The accuracy at area B was slightly better than that at area A. It seemed that the gain by the strong AP signals in area A was offset by that area's complex structure. Area A included a mixture of meandering paths and small- and medium-sized open spaces, whereas area B had a grid structure with relatively low ceilings.

To better understand accuracy fluctuation, we depicted the accuracy levels obtained at each location in a figure. Figure 5 shows this situation for the B1 level of the COEX area. The length of the bars at a location indicates the average error distance there. The blue and black bars represent the locations with good accuracy (less than 3 and less than 6 meters in error distances, respectively), and the violet and red bars represent the locations with bad accuracies (less than 9 and greater than 12 meters in error distances). As the two side graphs illustrate, the accuracy of localization depended on the distributions of the Wi-Fi signal strengths. The locations with strong signals (that is, locations near the peak of a particular AP signal) showed better accuracy than the locations with only weak or medium signal strengths.

As the figure illustrates, the locations with low accuracies were usually detected in combination with the locations with good or high accuracies, implying that if the trace data were correctly used, the effect of applying the filters would be great. Despite the system's inability to achieve 100 percent accuracy in the floor-level estimation, almost all of the inaccurate floor-level estimations were removed or deactivated, mainly by the application of the filters. The adaptive Kalman filter had the most prominent effect in this aspect. The delay filter was effective in controlling outliers because it could deactivate the display of locations if the newly estimated location deviated too far from the previous locations. The signal filter imputed missed AP signals for the captured Wi-Fi signals, which helped improve the overall localization accuracy. After activating all the filters integrated into the system, the displayed locations proceeded on the way network in a stable manner.

However, activating the filters caused a significant delay in response time. Most of this was caused by the delay filter. When we deactivated this filter, we could reduce the response time within around MST + 0.2 seconds, but it wasn't worth it. The users were more tolerant of the delay than of the possible incorrect location estimation.

Service Launching and User Feedback

After testing and evaluating a navigation system, the system should be integrated with a more general-purpose smartphone app so it can be distributed to users. Then, the app can collect, accumulate, and analyze user feedback to further improve the navigation system.

In the case of COEX, we integrated the COEX indoor navigation system into the myCoex app. The myCoex app provides general services such as exhibition and event notification, facility finding, and providing information about stores and offices within the complex as well as the indoor navigation service. The myCoex app was downloaded more than 200,000 times its first year, with approximately 20 percent of the downloads from abroad.

Meanwhile, the ever-changing AP environment is one of the nagging issues of Wi-Fi-based indoor localization and navigation systems. We addressed this problem to some extent by utilizing user feedback data. We confirmed that the addition of new APs and the removal of existing APs can be reflected to the WRM by analyzing the appearance patterns of APs in the feedback Wi-Fi fingerprints.[12] The feedback data was collected without the intervention of users while they were using the service. Meanwhile, the accuracy wasn't significantly influenced by a slight change of the AP environment—for example, from 10 to 20 percent. However, when the change was made for more than half of the APs, accuracy drastically degraded.

For a more precise WRM update, we need to assemble a sufficient number of fingerprint traces into long sequences and fit the assembled sequences into a known indoor map. Tagging the locations of the assembled fingerprint sequences by referencing only indoor maps is a challenging problem.

The reconfiguration of spaces, which frequently happens (particularly in exhibition areas), is another issue to be addressed. As a solution, the indoor map and its associated way network should be changed. Then, the WRM should be reconstructed. However, if the change occurs too frequently, this approach requires considerable time and cost. A walking survey, in which fingerprints are collected while collectors are walking in a space and the collected locations are later estimated for tagging the locations of the fingerprints, is one approach used to cope with this situation. Crowdsourcing is another. We developed a crowdsourcing WRM construction method to collect fingerprints of POIs through user participation.[13] Wi-Fi-SLAM[14] and Zee[15] incorporate the capability of smartphone-integrated sensors such as three-axis accelerometers, compasses, gyroscopes, and pressure sensors to build WRMs automatically.

The more user feedback data we have, the further we can enrich the services of the app. Identifying crowded or less crowded areas and analyzing visitors' moving patterns are possible for the valuation of POIs.

We can make the indoor navigation system more complete by incorporating pedestrian dead-reckoning techniques and using various sensors embedded in smartphones. For example, floor-level accuracy can be drastically improved with the help of a pressure sensor. In building a WRM, the crowdsourcing approach will play a critical role in reducing time and costs in the future.

We are currently developing a door-to-door navigation system, in which bus, subway, and train navigation systems are integrated with the indoor navigation system to direct users from a source to a destination, hopefully without any disconnection. Of course, several technical issues, including seamless integration of indoor and outdoor navigation systems, should be addressed to realize this system.

Yet the COEX system has already affected the marketplace. After experiencing the COEX navigation system, many customers and vendors recognize the potential of Wi-Fi-based indoor localization and navigation systems for their businesses. For example, Incheon International Airport decided to provide an indoor navigation service to help passengers find their way in the airport terminal, and some hospitals are applying localization technology to monitor the locations of doctors, nurses, staff, and even patients.

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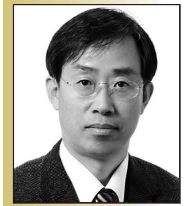

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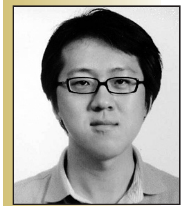

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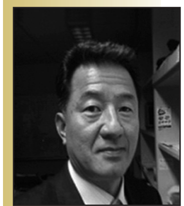

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