WSN-based Real-Time Indoor Location System at the Taipei World Trade Center: Implementation, Deployment, Measurement, and Experience

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Abstract—Given the popularity of location-based services today and the advances in indoor localization, we find it curious that the systems are rarely deployed for public use. Having implemented a RF-fingerprint-based location system at the Taipei World Trade Center (TWTC), we are able to examine quantitatively the system performance. In that, the 50-percentile localization error is approximately 6.2m. This is significantly larger than that of most testbed studies, indicating significant discrepancy between the results taken from fine-tuned testbeds vs. flash, in-situ deployments. We also find that dynamics in physical environment and RF signals impact the results more than the survey density, indicating a well-designed estimation method may alleviate the labor requirement for RF-fingerprint survey. Our measurement study is unique in that the area of deployment is large and the ‘window of opportunity’ for deployment is limited to a few hours. This we refer to as a ‘flash deployment’.

I. INTRODUCTION

With the increasing use of location-based services, meter-scale indoor localization has been a technology of interest and a subject of study. It has been more than a decade since the ground-breaking work [1]. There are plenty of studies reporting measurements from testbeds after repeated fine tuning. However, in real world environment, there are usually constraints limiting the settings of localization systems and some factors could not be adjusted after setup, which may affect the positioning accuracy [2][3][4]. What we find particularly interesting is that there exist very few indoor location systems serving the public on a regular basis [5][6].

Towards a better understanding of how the system performs in practice, we teamed up with the Taipei World Trade Center (TWTC) and deployed a location-based service that navigates the visitors through the exhibitions in the annual trade fair. The underlying location system is implemented based on the RF-fingerprinting approach. Relative to RF-propagation-model-based and dead-reckoning-based alternatives, this approach is more robust to heterogeneous or wide-area indoor environment. This is particularly the case given the booths in the trade fair are constructed by panels of different forms and materials. 24 RF beacons are placed at the strategic locations agreed by the building safety officer. The tracking area spans about 1390m². During the trade fair, we record the RF signals at 13 testing locations. The 50-percentile and 80-percentile error are 6.2m and 11.02m respectively. Further analysis of the data reveals that (1) change of the physical environment (before and after taking the RF fingerprints) may impact the 50-percentile results by 24.7%, (2) RF signal variation 32.3%, and (3) the fingerprint survey density 7.0%. In this particular deployment, the effects of the physical environment and the RF signal characteristics are more pronounced. This suggests that (1) adjusting the RF fingerprints continuously and (2) filtering the RF signals based on the statistical norm and/or additional sensor input will be more effective as improvements. Surveying the RF fingerprints at a higher density helps. The improvement in quantity, however, is relatively small. Location estimation methods that cope well with the environmental and RF signal variations are of higher relevance to pursue next.

Our contribution in this work is three-fold: a working implementation of the RF-fingerprint-based location system, a quantitative study of data collected from a unique in-situ deployment and a number of insights towards practical use of indoor location systems.

II. LOCALIZATION METHOD
We implement an RF-fingerprint-based localization system for the study. The idea of these RF-fingerprint-based solutions is to exploit the mapping between a tag's location and the radio signal strength (RSSI) received from a set of pre-deployed beacons. This set of RSSIs is referred to as the RSSI signature or vector. These systems typically operate in two phases, the training and tracking phases. In the training phase, the area is surveyed to construct the reference RSSI signature per sampled location. The collective set of RSSI signatures at various locations is referred to as the radio map. With the radio map, the system compares the collected RSSI vector to the reference RSSI signatures in the tracking phase to identify the closest possible location. In our implementation, we adopt the k-nearest-neighbor (KNN) method for location inference. In that, we select the top k sample locations whose RSSI signatures are the closest in Euclidean distance to the RSSI vector. The KNN estimator will output a location as an average of the top k locations' coordinates.

III. DEPLOYMENT

The indoor localization system was deployed in the Taipei World Trade Center (TWTC) Exhibition Hall No. 3. Collaborating with InfoExplorer [8], a Taiwan-based navigation solution developer, this system was part of the visitor navigation service for the Broadband Taiwan Expo, which took place on the 26-28th October, 2009. We are allowed 2 days to set up the system, the same as the participating companies had to set up their booths. We are allowed 3 days, also limited, for measurement. We refer to a deployment of such time constraint as a “flash deployment”.

The floor plan of the TWTC is shown in Fig. 1. It is an area of size 118m × 18m. The area where indoor location service is required is enclosed by the dashed line in Fig. 1, which is about 1390 m² large. There were 24 beacons installed.

The placement of the beacons were marked as stars in Fig. 1. The distribution of the beacons was not uniform due to the constraints that the beacons can only be placed in public space and the exact orientation is limited by the layout of the booths. See Fig. 2(a).

To facilitate the survey and to acquire radio map, we marked the grid points on the floor using a long rope with tape-marks every 1 meter apart. See Fig. 2(b). The rope was prepared in advance to speed up the process. As a result, we defined 240 grid points, shown as the dots in the service area in Fig. 1. To obtain the radio map, radio signal strengths are surveyed at all 240 grid points in 4 orientations.

There were 13 locations chosen to conduct the testing in measurement phase, referred to as “testing points”. These are the croses at the intersections of the aisles in Fig. 1. At each testing point, 450 samples were recorded in each of the 4 orientations, which resulted in a total of 23400 location estimations. The exact locations and orientations were also recorded as the ground truth to estimate the localization errors.
IV. Experiment

The devices used at TWTC included 24 beacon nodes and a number of receiving tags. To collect the radio map and the testing data, a data logger was also used. The key component of both the beacon node and receiving tag was Taroko. It was a Telos-like sensor board equipped with a TI MSP430 microcontroller, a CC2420 802.15.4 radio chip, an FT232 USB serial port IC, and an 8Mbit flash memory chip.

For a beacon node, one Taroko board and two C batteries were packed into a plastic case of size 8cm × 8cm × 5.5cm. See Fig. 3(a). The batteries can sustain the beacon node up to 12 days, which was sufficient for the task at hand. For a tag node, one Taroko board and a Lithium rechargeable battery were packed into a custom-made plastic case of size 8.3cm × 3.7cm × 1.7cm. See Fig. 3(b). The tag was worn like a visitor’s badge around the user’s neck. The Lithium battery can be recharged by connecting the tag node to any power sources via the USB interface. To collect measurement data, we connected the tag and uploaded the signal strength information via the USB interface to a lightweight laptop.

V. Results

Using the 23400 samples collected, we calculate the corresponding localization errors. As a base for comparison, we implement a simple random number generator and generate 23400 random grid point numbers as results of a naïve localization method. This is the worst-case in effect. Fig. 4 depicts the cumulative distribution function (CDF) of the localization error from the RSSI-based and random location estimations. The 50-percentile errors of the two methods are 6.2m and 26.57m, and the 80-percentile errors are 11.02m and 47m respectively. The results show that the RSSI-based location system works substantially better than random guesses. However, the scale of the localization errors from the TWTC deployment is significantly larger than that of most testbed studies [1][2][7], indicating a significant degree of discrepancy between the results taken from fine-tuned testbeds vs. flash, in-situ deployments.

VI. Analysis

A. Effect of Environmental Change

Having observed a significant degree of changes in the panels and booths installed, as well as a number of visitors in the event, vs. pre-event preparation, one of our major concerns is that the radio map surveyed in the pre-event days might not be representative of the in-event days. To examine the effect of environmental changes, RF signals in the radio map are strategically selected as testing data for pre-event location estimation, whereas RF signals taken at testing points in the measurement phase are used for the in-event location estimation. More specifically, we use 10-fold self-testing on the radio map data for the former. By 10-fold self-testing, we take 9/10 of the data to derive radio map as the training set and the other 1/10 as the testing set. Under such a manipulation, the training and testing sets are measured at the same time. The environmental change is supposedly minimal. Therefore, by comparing the localization errors derived this way to the errors obtained in Section V, we shall observe the effect of environmental changes to localization error.

The CDFs of pre-event and in-event localization error are depicted in Fig. 5. The 50-percentile errors are 4.67m and 6.2m, and the 80-percentile errors are 9m and 11.02m respectively. These results indicate that if the environmental changes in the TWTC event can be captured in the survey, the 50-percentile and 80-percentile error may be reduced by 24.7% and 18.3%.

B. Effect of Signal Variation

Another observation on the fine details of the RF signals collected is that the RF signal strength variation can be large. To understand the effect of this factor in the system, we explore a hypothetical extreme, where we set the testing RSSI vector to be the same as the reference signature of a location.
Fig. 6 shows the CDFs of the hypothetical-extreme and pre-event localization error. The 50-percentile errors are 3.16m and 4.67m, and the 80-percentile errors are 5.34m and 9m respectively. These results indicate that by minimizing the signal strength variation, the 50-percentile and 80-percentile error may be further reduced by 32.3% and 40.7%.

C. Effect of Survey Density

It is commonly known that a dense survey usually result in a high level of localization accuracy. A dense survey is however labor intensive for the Broadband TW Expo 2009 scenario. To examine the influence of survey density, we calculate the localization errors with a different grid spacing.

Fig. 7 depicts the CDFs of localization error with different survey density. The 50-percentile errors for 1m and 8m grid spacing are 6.2m and 6.67m, and the 80-percentiles are 11.02m and 13m respectively. Quantitatively speaking, reducing the grid space from 8m to 1m reduces the 50-percentile and 80-percentile errors by not much, 7.0% and 15.2% only.

VII. SUMMARY AND OUTLOOK

Despite the advances in indoor localization technology, there exist rarely sizeable deployments for public use. We implemented a RF-fingerprint-based location system at the Taipei World Trade Center (TWTC) and examined quantitatively the system performance. The 50-percentile localization error is 6.2m. This is significantly larger than that of most testbed studies, indicating a significant level of discrepancy between the results taken from fine-tuned testbeds vs. flash, in-situ deployments. We also find that dynamics in physical environment and RF signals impact the results more than the survey density, suggesting a well-designed estimation method is more critical. In particular, (1) adjusting the RF fingerprints continuously into the tracking phase and (2) filtering the RF signals based on the known statistical norm and/or additional sensor input will be more effective as improvements. Surveying the RF fingerprints at a higher density helps. The improvement in quantity, however, is relatively small. Location estimation methods that cope well with the environmental and RF signal strength variations are of higher relevance to pursue towards practical use of large-scale localization system.

REFERENCES


