Sensor-Assisted Wi-Fi Indoor Location System
for Adapting to Environmental Dynamics
Acknowledgments

This thesis is the result of two and half years of work whereby I have been supported and encouraged by many people. I would like to express my gratitude to all of them.

I want to thank the Department of Computer Science and Information Engineering of National Taiwan University for providing me an ideal environment to commence my studying on this subject. This is a wonderful department with excellent professors, outstanding colleagues, and abundant resources. Not only has it enabled me to concentrate on research without worrying about financial problem, I can ask for advice from knowledgeable professors and brainstorm ideas with my colleagues.

I am deeply indebted to my supervisor Prof. Hao-hua Chu whose help, inspiration, and encouragement have helped me throughout this thesis research. I have also received valuable assistance from Prof. Jane Yung-jen Hsu and Prof. Polly Hung. Their comments and guidance have motivated me to carry out further exploration and discovery into my thesis topic.

I would like to thank my colleagues Ji-Rung Chiang, Chuang-wen You, Li-Wei Jan, and Chia-nan Ke for their friendship, support, and suggestion. I am especially grateful to Ji-Rung Chiang who has offered tremendous support during the time of difficulty.
A lot of experimental data were collected to support my thesis. Many people spent a great amount of time to help me conduct these experiments. Wan-Rong Ji, Ji-Rung Chiang, Chuang-wen You, Hun-Yuan Yeh, Ko-Chih Wang, Shin-jan Wu, Chia-nan Ke, Shao-you Cheng, and Chia-Nan Yen had all made great contribution to these experimental data. There were numerous times when, under my request, they stayed late to continue these exhaustive experiments.

A team from Industrial Technology Research Instituted (ITRI) also contributed to the development of this work. Arvin Wen Tsui and his team provided a tool to develop Wi-Fi based localization system and they also gave many insightful suggestions for how to improve my thesis research.
Abstract

Wi-Fi based indoor location systems have been shown to be both cost-effective and accurate, since they can attain meter-level positional accuracy by using existing Wi-Fi infrastructure in the environment. However, two major technical challenges persist for current Wi-Fi based location systems: instability in positional accuracy due to changing environment dynamics, and the need for manual offline calibration during site survey. To address these two challenges, three environment factors (doors, humidity, and human cluster) that can interfere with radio signals and cause positional inaccuracy in the Wi-Fi location systems are identified. Then, we propose a sensor-assisted adaptation method that employs environment and proximity sensors to adapt the location systems automatically to the changing environment dynamics. In addition, a collaborative method is applied to leverage more accurate location information from nearby neighbor nodes to enhance the positional accuracy of a human cluster. Experiments were performed on the sensor-assisted adaptation and collaboration methods. The experimental results show that our enhancement can avoid adverse reduction (43.7% ~ 236.6%) in positional accuracy that can often occur in conventional non-adaptive & non-collaborative methods under changing environment dynamics.
Contents

Acknowledgments i
Abstract iii
List of Figures vii
List of Tables ix

Chapter 1 Introduction 1
  1.1 Environment Dynamics 3
  1.2 Further Analysis on Human Clustering Problem 7
  1.3 Sensor-assisted Adaptation & Collaboration 10

Chapter 2 Related Work 15

Chapter 3 Sensor-Assisted Adaptive Localization 20
  3.1 Sensor-assisted Sample Collection Phase 20
  3.2 Online Calibration Phase 24
  3.3 Adaptive Localization Phase 25
Chapter 4  Sensor-Assisted Collaborative Localization  26
  4.1  Neighborhood Detection ................................. 28
  4.2  Confidence Estimation ............................... 28
  4.3  Collaborative Error Correction ...................... 29

Chapter 5  Experiments  32
  5.1  Performance Evaluation on RFID-assisted Online Calibration  .... 33
  5.2  Performance Evaluation on Adaptive Localization ................. 35
    5.2.1  Impact of Closed/Open Doors ...................... 36
    5.2.2  Impact of Relative Humidity ....................... 39
  5.3  Performance Evaluation on Collaborative Localization ........... 41

Chapter 6  Conclusions and Future Work  45

Appendix A  Yi-Chao Chen’s Publications  47

Bibliography  49
List of Figures

1.1 Floor layout for measuring the impacts of environment factors. . . . . . . 3
1.2 the RSSI distribution in open vs. closed doors scenarios . . . . . . . . . 4
1.3 the RSSI distribution in 40% relative humidity level vs. 70% level . . . 5
1.4 the RSSI distribution in human cluster vs. no human cluster scenarios 6
1.5 CDF of the cluster’s average positioning errors . . . . . . . . . . . . . 8
1.6 CDFs of each node’s average positioning error within a 7-person cluster 9
1.7 Adaptive Location Positional System . . . . . . . . . . . . . . . . . . . 11

3.1 Three phases of sensor-assisted adaptation . . . . . . . . . . . . . . . . 21
3.2 Estimate the location of RSSI samples . . . . . . . . . . . . . . . . . . . 23

4.1 Design of collaborative location system . . . . . . . . . . . . . . . . . 27
4.2 Confidence scores and location estimation errors . . . . . . . . . . . . . 30

5.1 Floor layout for the first experiment . . . . . . . . . . . . . . . . . . . 33
5.2 Average positional accuracy with increasing training traces . . . . . . 34
5.3 Site survey in the offline training phase. The red squares (■) mark
the sampled locations. . . . . . . . . . . . . . . . . . . . . . . . . . . . 35
5.4 the impact of close/open doors on the average positioning errors with increasing training samples under different map-environment combinations ........................................ 37
5.5 CDFs of the average positioning errors in different close/open doors scenario ................................................................. 38
5.6 the impact of humidity (40% and 70% RH levels) on the average positioning errors with increasing training samples under different map-environment combinations ........................................ 39
5.7 CDFs of the average positioning errors in different humidity (40% and 70% RH levels) scenario .................................................. 40
5.8 CDFs of average positioning errors in the 3-person cluster scenario . 42
5.9 the amount of accuracy improvement versus the neighborhood confidence difference in the 3-person dense cluster ........................................ 43
5.10 CDFs of average positioning errors in the 7-person cluster scenario . 44
5.11 the amount of accuracy improvement versus the neighborhood confidence difference in the 7-person dense cluster ................................. 44
List of Tables

1.1  Average Position Accuracy Under Changes in Different Environment Factors ........................................ 7

5.1  Impact of Open/Close Doors on Average Positional Accuracy ...................................................... 38

5.2  Impact of Humidity Levels on Average Positional Accuracy ......................................................... 40
Chapter 1

Introduction

Location is one of the most widely utilized context data in context-aware and ubiquitous computing applications. To support such location-aware applications in the indoor environment, many indoor location systems [10] have been developed in the past decade with different deployment costs and positional accuracy levels. A promising approach is the Wi-Fi based location estimation system, which is cost effective by employing existing IEEE 802.11 network infrastructure available in many office and home environments. The proposed approach can provide meter-level accuracy, which is sufficient for most location-aware applications. For instance, the state-of-the-art Wi-Fi based location system (e.g., Ekahau location system [5]) claims to attain a positional accuracy of up to 1 meter.

Wi-Fi based location systems generally work in two phases. Phase 1 is called the offline training phase, in which a human operator performs a site survey by measuring the received signal strength indicator (RSSI) from various different access points (APs) at some fixed sampled points in the environment. These RSSI measurements are recorded onto a radio map that depicts the RSSI values of APs at different sampled points. Phase 2 is known as the online estimation phase, in which the target’s
location is calculated in realtime by matching a sampled point (or several sampled points) on the radio map with the closest RSSI values to the target.

Current Wi-Fi based location systems have two general problems [4]. The first problem is the amount of manual calibration effort needed to build the radio map during the offline training phase. Users must compile a fairly dense radio map comprising many RSSI measurements at many sampled points to obtain reasonable positional accuracy. For example, the Ekahau location system [5] requires 80 RSSI samples to be taken every 3 meters to attain an average positional accuracy of 3 meters in a 1000 $m^2$ environment, which translates into approximately two man-hours of calibration effort.

The second problem is the instability in the positional accuracy due to the changing environment dynamics. The following three dynamic factors have been observed to change frequently over time in the environment, affecting the positional accuracy: humidity level, people presence and movements, and open/closed doors. These environment factors can interfere with the radio signal propagation from the APs to the target mobile devices, varying the received RSSI. For example, radio signals attenuate more rapidly at a higher humidity level, when a crowd of people (i.e., human clusters) are blocking radio signal path between APs and target mobile devices, or when the floor plan changes due to doors opening and closing. These dynamic environment factors can incur location estimation errors in the existing Wi-Fi based location systems that construct and maintain only one static radio map, because this single radio map is calibrated by the environment condition at the time of site survey. When the environment condition changes later, this static radio map may no longer reflect the expected RSSI values in the environment.
1.1 Environment Dynamics

To determine the quantitative effects of these dynamic environment factors, preliminary experiments were performed in a corridor on the 6th floor of our department building shown in Figure 1.1. The corridor is marked in green. Five IEEE 802.11b access points (marked as red triangles ▲) are placed inside five rooms along the corridor. At any given location on the corridor, a client mobile device can receive radio signals from about 4–10 access points simultaneously. Some radio signals come from access points located on different floors. The effects of the following three environment factors (open/closed doors, humidity level, and human clusters) on the RSSI and the positional estimation accuracy were analyzed based on this environment.

Figure 1.1: Floor layout for measuring the impacts of environment factors.

- **Impact of Open/Closed Doors:** Open and closed doors have a similar effect to changes in the environment’s floor layout, since they affect the radio signal path traveled from access points to the target mobile device. Consider the floor layout in our department building depicted in Figure 1.1. Since a Wi-Fi access point is placed in each room along the corridor, open or closed doors are expected to significantly affect the RSSI received by the target mobile device on the corridor. To determine how doors impact RSSI, the following experiment
was performed: (1) 300 RSSI samples were continuously collected in both the open-all-doors and close-all-doors scenarios from the one location point on the corridor, and (2) the probability distribution of these RSSI samples were plotted as shown in Figure 1.2. The measurement results demonstrate a significant rise of 9 dBm on the average RSSI from the close-all-doors scenario to the open-all-doors scenario.

Figure 1.2: the RSSI distribution in open vs. closed doors scenarios

- **Impact of Changing Humidity Levels:** The IEEE 802.11 specification adopts a radio frequency of 2.4 GHz, which is also the resonant frequency of water. Hence, an environment with a high relative humidity (RH) level tends to absorb more power from the radio signals than in lower relative humidity level. To measure the effect of humidity on the RSSI values, the following experiment was performed: (1) 300 RSSI samples were continuously collected at both the higher RH level (70%) and the lower RH level (40%) at the same fixed location point on the corridor, and (2) the probability distribution of
these RSSI samples were plotted, as shown in Figure 1.3. The measurement result demonstrates that the average RSSI value falls by 0.8 dBm from 70% RH level to 40% RH level.

Figure 1.3: the RSSI distribution in 40% relative humidity level vs. 70% level

- **Impact of human clusters:** The presence of human clusters has a similar effect to obstacles blocking radio signals. The following common people-blocking scenario in a museum was emulated in this experiment. A museum tracks the location of Joe, a visitor, through his mobile device. When Joe stops in front of a popular painting exhibition, other visitors who are interested in that painting exhibition are standing around him, forming a human cluster. These stand-around visitors are likely to block the radio signals from the APs to Joe’s mobile device. To determine how human clusters impacts RSSI, we have performed the following experiment: (1) a formation of six people was arranged surrounding a user carrying the target mobile device; (2) a fixed location point (marked as ★ in Figure 1.1) was chosen on the corridor, and 300 RSSI samples were continuously collected, and then (3) the probability distri-
bution of these RSSI samples was plotted, as illustrated in Figure 1.4. The measurement result demonstrates that in a human cluster scenario, the RSSI values attenuate rapidly. The average RSSI value is reduced by approximately 8 dBm from the no human cluster scenario to the human cluster scenario.

Figure 1.4: the RSSI distribution in human cluster vs. no human cluster scenarios

Table 1.1 summarizes how dynamic environment factors influence the positional accuracy. The radio map is calibrated under the environment condition of no human cluster, close-all-doors, and 40% relative humidity level, denoted as the baseline radio map. The average positional accuracy using the ITRI positional engine [12] is 2.13 meters. This number serves as the baseline for comparison with other scenarios under various environmental conditions. In the human cluster scenario, the average positional accuracy deteriorates by 85.9% to 3.96 meters. In the open-all-doors scenario, the average positional accuracy deteriorates by 236.6% to 7.17 meters. When the RH level rises to 70% (e.g., on a raining day), the average positional accuracy deteriorates by 43.7% to 3.06 meters. Although the effect of humidity
1.2. FURTHER ANALYSIS ON HUMAN CLUSTERING PROBLEM

Table 1.1: Average Position Accuracy Under Changes in Different Environment Factors

<table>
<thead>
<tr>
<th></th>
<th>Baseline: Training environment condition: non-blocking people, close-all-doors, 40% relative humidity level</th>
</tr>
</thead>
<tbody>
<tr>
<td>Changing Environment</td>
<td>No change</td>
</tr>
<tr>
<td>condition</td>
<td>70% humidity level Scenario</td>
</tr>
<tr>
<td>Human cluster</td>
<td>3.96 meters (85.9%)</td>
</tr>
<tr>
<td>Effect on Positional</td>
<td>2.13 meters</td>
</tr>
<tr>
<td>accuracy</td>
<td>3.06 meters (43.7%)</td>
</tr>
<tr>
<td></td>
<td>7.17 meters (236.6%)</td>
</tr>
</tbody>
</table>

is not as significant as that of human clusters and doors, the change in humidity level still introduces an error of almost one meter to the existing static methods. In order to enhance the positional accuracy, the positional engine needs to adapt to the changing environmental factors. Our adaptive approach is to (1) utilize sensors to detect changes in these environmental factors, (2) train multiple radio maps corresponding to different environmental settings, and (3) select a closest matching radio map to the current environmental setting for location estimation.

1.2 Further Analysis on Human Clustering Problem

Since the human clustering factor is more dynamic than the other two environmental factors (open/closed doors and changing humidity level), i.e., depending on the size of the human cluster and the relative position of the target node within the human cluster, we have performed further experiments to measure effect of human clustering on the positional accuracy. This experiment is based on Ekahau [5] positional engine. For each test, users stand at pre-specified positions to form clusters of sizes 1, 3, and 7 person(s). Each user carries a Notebook PC equipped with a wireless network card to collect RSSIs from APs. The same Wi-Fi cards are used to minimize errors
CHAPTER 1. INTRODUCTION

Figure 1.5: CDF of the cluster’s average positioning errors due to different signal strength interpretations by different WiFi card drivers. The results are plotted in Figure 1.5, showing that the positional accuracy degrades significantly with an increasing cluster size. In a single person case (no clustering), Ekahau can achieve a high positional accuracy of approximately 80% within an error of 2 meters. In comparison, Ekahau’s positional accuracy degrades to 60% in the case of 3-person clusters, and further degrades to less than 30% in the case of 7-person clusters. The general trend is that increasing cluster size leads to rapidly decreasing average positional accuracy and precision.

To investigate how clustering influences the positional estimation accuracy for each individual in a cluster, we have plotted cumulative density functions (CDFs) of average positional errors experienced by each individual in Figure 1.6. It shows a 7-person clustering case where each colored curve represents the positional accuracy experienced by one person in a cluster. The relative position of each person
in a cluster is shown in a small diagram at the bottom. Although clustering degrades average positional accuracy of a cluster (shown in Figure 1.6), the amount of degradation experienced by people varies within the same cluster. In the 7-person clustering case shown in Figure 1.6, user-7’s accuracy is almost unaffected, whereas user-3’s accuracy is significantly reduced.

The next question is what causes such large variance in positional accuracy among individuals within the same cluster? We have found several possible direct and indirect causes, such as people’s relative position within a cluster, their orientation, the way (e.g., the height) they hold the device, the geometry of the environment, etc. Rather than considering human clustering as a hindrance to improving accuracy in localization systems, we can turn them into an advantage by exploiting collaboration among neighbor nodes. Collaborative localization leverages the variance in location accuracy among nodes within a cluster. By identifying nodes with high location accuracy, we can use their location estimations to help better localize neighbor nodes with lower location accuracy.
CHAPTER 1. INTRODUCTION

There is another reason for the need of collaborative localization: sensor-assisted adaptation approach requires constructing different radio maps corresponding to different environment settings. However, it is impossible to model or enumerate all possible cases of human clustering formations, human orientations and moving speeds, and further, to construct corresponding radio maps. Therefore, our location system incorporates both adaptive and collaborative localization to address complex human clustering.

1.3 Sensor-assisted Adaptation & Collaboration

One naïve effective approach to the issue of instable positional accuracy is to construct and calibrate multiple context-aware radio maps under different environment variations, enabling the system to monitor the current environment condition, choose the optimally matched radio map to current state of environment condition, and use it to estimate the location. Unfortunately, this approach resolves the positional accuracy problem at the expense of further increasing the level of user calibration effort required to construct these context-aware radio maps. Calibrating multiple context-aware radio maps is problematic in two ways: (1) constructing $n$ context-aware radio maps requires repeating the same RSSI sample collection $n$ times, and (2) manipulating environment conditions, (e.g., changing humidity levels in a large facility or assembling various sizes of block-around people at different locations, is non-trivial. These two difficulties make this approach unworkable.

To overcome these two difficulties, a solution is proposed to adapt sensors to help generate these context-aware radio maps without the need either (1) to manually calibrate these context-aware radio maps, or (2) to manipulate multiple environment conditions. The proposed method adopts a subset of RSSI samples obtained over
1.3. SENSOR-ASSISTED ADAPTATION & COLLABORATION

The course of its online usage to automatically train these context-aware radio maps. Our sensor-assisted adaptation comprises four phases depicted in Figure 1.7 and described below. These phases are different from those (calibration & estimation) in current Wi-Fi based location systems.

Phase 1 is the sensor-assisted sample collection phase. A relatively light sensor infrastructure is deployed (or an existing sensor infrastructure is adopted) in the environment to help label specific RSSI samples during the system’s online usage. This sensor infrastructure includes two categories of sensor. The 1st category is the RFID infrastructure, which is utilized to infer the locations on some selected RSSI samples (specifically, constant-speed walking samples described in detail description in Section 1.3), and to label these selected samples with the location information. The 2nd category comprises environment sensors to detect different environmental conditions (e.g., a humidity sensor to detect the humidity level) under which these selected RSSI samples are collected, and again to label these samples with the environmental condition state. These labeled RSSI samples are sent to the next phase to train context-aware radio maps. Notably, the proposed method does not require setting up all possible environmental conditions since the system encounters various environment conditions during its online usage. Then, the location system can collect RSSI samples under these environmental conditions and learn their context-
Phase 2 is the *online calibration phase*, which applies the labeled RSSI samples to train different context-aware radio maps. Notably, the location system may encounter a new environmental condition or have insufficient samples to provide sufficiently accurate location estimation during its online usage. However, as more RSSI samples are collected under different environmental conditions over the course of its online usage, the system’s accuracy gradually improves both in the *higher number of accurate (quality) radio maps* trained with more RSSI samples, and larger *quantity* of context-aware radio maps with finer-grained environmental conditions.

Phase 3 is the *adaptive localization phase*. The system initially queries the current environmental condition state from environment sensors (e.g., from the humidity sensor). Then, the system finds one radio map from the set of *context-aware radio maps* that best matches the current environment condition. This optimally matched radio map is utilized to estimate the locations of the target mobile devices. The system also produces a *confidence* score, which measures the probability of its location estimation being accurate.

Phase 4 is the *collaborative localization phase*. The system first identifies nearby neighbor nodes that may have higher location estimation *confidence* score than the target node. Then, the target node’s location estimation is enhanced using the estimated locations of higher confident neighbor nodes.

To our knowledge, no known existing Wi-Fi based location systems utilize sensors to effectively overcome environmental dynamics and to enhance the positional accuracy. This work is believed to be the first to adapt sensors to detect variations in the physical environment factors, apply them to automatically calibrate multiple context-aware radio maps from online samples, and incorporate adaptation and collaboration into estimating the Wi-Fi based location.
The remainder of this paper is organized as follows. Section 2 describes related works. Section 3 explains the sensor-assisted adaptation to overcome environmental dynamics. Section 4 describes the sensor-assisted collaboration to overcome human clustering. Section 5 presents the experimental results and shows the improvement in positional accuracy in our approach. Section 6 draws the conclusion and suggests future work.
Chapter 2

Related Work

Many location estimation systems have been developed using Wi-Fi RSSI values for. These systems can be categorized into two broad approaches. The first approach is based on the deterministic method [2][12][5]. Systems following this approach apply deterministic inference, such as triangulation and k-nearest-neighbors (KNN) search, to estimate the target device’s location. For example, the RADAR system [2][1] applies KNN to obtain the $k$ nearest neighbors, where a neighbor is a sampled point on the radio map, and nearness is defined as closeness between the target device’s RSSI values and the RSSI of any sampled points on the radio map. To estimate the location of the target device, the deterministic approach can be used to average the locations from the $k$ nearest neighbors. The second approach is based on the probabilistic method [21][11][18][6]. Seshadri et al. [21] applied Bayesian’s inference, which uses multiple probabilistic models and histograms to enhance the performance of the original system, by calculating the conditional probabilities over locations based RSSI. They added a motion model to describe the continuity in human’s movements such that it can lower the oscillatory location estimations in Wi-Fi based localization systems. Notably, our proposed sensor-assisted adaptation
is independent of these two approaches, and can be applied to both approaches and further enhance their positional accuracy under environment dynamics. Additionally, both approaches need manual offline site survey, and therefore can also benefit from our proposed online calibration system.

To achieve a high level of accuracy, Wi-Fi based location systems need a detailed offline site survey to collect numerous training samples to calibrate an accurate radio map [24], which is a time consuming process involving manual user efforts. Several alternative methods to offline site survey that do not require users to collect RSSI samples manually have been proposed. For example, the RADAR system [2][1] has applied the radio propagation model [20][23][8] to estimate the RSSI at different locations in the environment. The radio propagation model can estimate the level of signal strength fading by analyzing the floor layout, locations and sizes of obstructions, and the attenuation factors associated with these obstacles. Rather than manually measuring RSSI samples in the environments, these systems adopt the radio propagation model to (1) estimate RSSI values for different location points, and (2) compile them into the radio map. However, in practice, the layout of an indoor environment is dynamic. Additionally, the attenuation factors of materials and obstructions are difficult to determine accurately. Moreover, some mobile obstacles can also influence Wi-Fi RSSI from AP to target devices, but their locations are not known in the offline phase. Based on their experimental results, the radio propagation model achieves a lower average positional accuracy of 4.3 meters than the manual site survey, with 2.94 meters average accuracy. Chai et al. [3] presented a method to lower the amount of user calibration efforts by reducing the quantity of RSSI samples needed during offline site survey. The reduction targets (1) the number of sampled points on the radio map, and (2) the number of RSSI samples gathered at each sampled point. After reducing the number of sampled points, they
apply simple interpolation method to estimate the RSSI values on the missing sampled points. They have reported that by reducing the number of sampled points and samples to 1/3 of the original site survey, the average positional accuracy, using their method, is only lowered by 16%~6%. Although their proposed system reduces the amount of user calibration effort while preserving system accuracy, it is still considered to be an offline calibration. By comparison, our proposed system is based on online calibration.

The instability in the positional accuracy in current Wi-Fi based location systems is largely due to constructing only one static radio map at the time of the site survey and under the environment condition at that time. Consequently, most such location systems cannot adapt to the changing environment conditions without conducting another site survey. Some proposed methods have attempted to address this issue. The temporal prediction approach in [24] can observe and learn how a radio map changes over time by employing emitters and sniffers to observe the Wi-Fi RSSI variations. By applying regression analysis, the temporal prediction approach can learn the temporal predictive relationship between the RSSI values received by sniffers and those received by the target mobile devices. However, the passage of time by itself cannot directly interfere with radio signal propagation and impact the positional accuracy. The direct causes of such interference are the physical environmental factors (such as the three factors described above: people, doors and humidity level) that change over time. Rather than analyzing and modeling the impact of these physical environmental factors on the positional accuracy, the temporal prediction approach assumes that the changes in these factors follow predictable temporal patterns. Although possibly valid in some environments, this assumption may not apply to many others. For example, the open & closed doors may be random, depending on the last person entering or leaving the room.
and whether she/he tends to open/close the door behind her/him. The occurrence time and size of human cluster are also difficult to predict in our department, since different numbers of visitors come and go anytime during the day.

The idea of utilizing neighbor information to help localization is also used in sensor network localization and network coordination. DOLPHIN [13] deployed fixed nodes with ultrasonic and RF sensors in an environment. Nodes with known location coordinates are called master nodes. Non-master nodes can compute their relative locations to multiple master nodes by exchanging ultrasonic and RF signals. After performing iterative triangulation, nodes can get their absolute coordinates and become master nodes. He et al. [9] proposed a cost-effective, range-based localization approach called APIT for large scale sensor networks. Like the DOLPHIN system, the sensor network contains anchor devices that can obtain their locations through GPS receivers. Anchor nodes first broadcast their locations to non-anchor nodes. A non-anchor node then iteratively chooses different combination of three received anchor nodes and performs a Point-In-Triangulation (PIT) Test, which is used to determine whether a non-anchor node is inside a triangular region formed by three anchor nodes. If a non-anchor node resides in that triangular region, that region is marked as a possible location of the non-anchor node. After all combinations are exhausted, the center of intersections from all possible regions is calculated to estimate a non-anchor node’s location. AFL [16] is a fully decentralized, anchor-free approach, utilizing the idea of fold-freedom to build a topology of a sensor network through local node interactions. In AFL, nodes start from a random initial coordinate assignment. By applying mass-spring optimization repeatedly, nodes’ location estimations can converge to be near their true coordinates. Our work differs from these systems in that they assume nodes with known locations are stationary, whereas our work assumes that nodes are mobile people. In addition, these sensor
network location systems assume that nodes with a cluster will not interfere with each other’s positional accuracy. However, in our system, people clustering results in blocked signals and degradation in positional accuracy.

Given the readily availability and cost effectiveness of RFID technology, several recent studies [19][7][14][15] have proposed using RFID to track locations. Willis et al. [19] attached passive RFID tags with known locations to the carpet pads, and RFID readers in the shoes to read locations off these passive RFID tags. To reduce the manual efforts of deploying tags, Haehnel et al. [7] used a robot to explore and localize the RFID tags in the space. The LANDMARC system [14] placed active RFID tags on the objects and RFID readers in the environment to track the tags. The GETA Sandals [15] are a footprint-based location system that tracks user locations by embedding ultrasonic sensors and RFID readers inside the sandals. Our proposed method also adopts the RFID technology to enhance the accuracy of the Wi-Fi location systems.
Chapter 3

Sensor-Assisted Adaptive Localization

The sensor-assisted adaptive localization is based on the following two concepts: (1) it applies sensors to construct context-aware radio maps, and adapts location estimation to environmental dynamics by choosing a radio map that best matches the current environment condition, and (2) it conducts online calibration to automatically gather RSSI samples and to train these context-aware radio maps, saving user efforts. Figure 3.1 shows the architecture of the proposed system, which consists of the following three phases, sensor-assisted sample collection phase, online calibration phase, and adaptive localization phase, which are described in detail below.

3.1 Sensor-assisted Sample Collection Phase

The idea behind the sensor-assisted online sample collection comes from the observation that when a person walks from a starting point to an ending point, his movement speed usually remains fairly consistent over the distance traveled. This
phenomenon is known as constant-speed walking. Other cases exist, including stopping in the middle of the path to talk to other people, or hurrying to attend a meeting. In these cases of non-constant-speed walking, the person completes the distance traveled in a different amount of time from the constant-speed walking. The constant-speed walking cases can be found from the walking distance (e.g., \( l \) meters) and the average walking speed of an individual (e.g., \( v \) meters per second) by checking whether the time traveled (\( t \)) falls within the range of normal constant-walking time of that individual (\( t \approx l/v \)). If that individual walks at a constant speed over a distance segment, then the system can accurately approximate the locations of RSSI values obtained on that walking segment from the following observable parameters: time of RSSI collection (\( t_i \)), walking velocity (\( v \)), starting and ending locations over this walking segment (\( (l_0, l_n) \)), and starting and ending times of the walking segment (\( (t_0, t_n) \)).
A small number of passive RFID readers [22] with known location coordinates were placed at the specified corners of the corridor to obtain these parameters. Additionally, the target mobile device was attached to a passive RFID tag, enabling it to be read when coming within approximately 2 meters of the passive RFID readers. A person’s walking path is divided into multiple walking segments, where each segment is defined as walking from one RFID reader placed at one corner to another RFID reader placed at another corner. The system then observes \((t_0, t_i, t_n, l_0, l_n)\) and derives the constant walking velocity \((v = (l_n - l_0)/(t_n - t_0))\). These parameters are then forwarded to the online RSSI sample filter.

The online RSSI sample filter checks whether the RSSI samples collected over a walking segment are from constant-speed walking; RSSI samples which are not are filtered out as training samples for the radio maps. This detection is conducted by checking whether the traveled time over a walking segment falls within the range of constant-speed walking time. The constant walking speed range was set to 1.25 m/s \(1.78 \text{ m/s}\). This range is based on measurement results from a pedestrian walking study [17], which shows that the average walking speed is approximately 1.51 m/s, and that the 15th percentile speed is 1.25 m/s. The 1.25~1.78 m/s range captures approximately 70% of people’s constant-speed walking and filters out almost all non-constant-speed walking. A fairly conservative range was selected to prevent RSSI samples from non-constant-speed walking from passing through the filter and corrupting the training samples. Since the training samples are gathered online and are fairly abundant, the quantity of RSSI training samples is considered much less important than the accuracy (or quality) of the RSSI training samples.

After the constant-speed walking RSSI samples are selected, the next step is the RFID-assisted location estimation that approximates the location of these RSSI values based on walking distance. Figure 3.2 depicts an example of using this method.
Two RFID readers are placed in \((x_0, y_0)\) and \((x_4, y_4)\). At \(t_0\), a user walks past \((x_0, y_0)\) which denotes the beginning of this walking segment. The user then reaches \((x_4, y_4)\), which denotes the end of this walking segment, and at time \(t_4\). Parameters \(SS_1\), \(SS_2\) and \(SS_3\) denote RSSI values collected at times \(t_1\), \(t_2\), and \(t_3\) over this walking segment. The position coordinates \((x_i, y_i)\), where \(i = 1, 2, 3\), can be estimated from these observable parameters according to the formulas defined below:

\[
\begin{align*}
  x_i &= x_0 + (t_i - t_0) * v_x \\
  y_i &= y_0 + (t_i - t_0) * v_y \\
  v_x &= (x_4 - x_0) / (t_4 - t_0) \\
  v_y &= (y_4 - y_0) / (t_4 - t_0)
\end{align*}
\]

where \(i = 0-3\)

Figure 3.2: Estimate the location of RSSI samples

Note that RFID-assisted location estimation does not replace the Wi-Fi location estimation engine for two reasons. First, RFID-assisted location estimation is based on post-analysis, and not in real time – the RFID-assisted location estimation is performed when the user has completed a walking segment. Second, RFID-assisted location estimation can only be adopted to calculate locations during constant-speed walking, while the Wi-Fi location systems need to work under all cases.

Environment sensors were also deployed to monitor the environmental condition state in terms of doors, humidity, and people. Humidity sensors were installed in the environment to detect the current humidity level. The open/close door status was obtained by connecting to the RFID/smart card access control systems already installed in most rooms occupied by the department labs. Zigbee proximity sensors were used to detect block-around people in a human cluster.
These RSSI measurements are labeled with (1) locations and (2) environmental condition to calibrate context-aware radio maps as described in the next phase.

### 3.2 Online Calibration Phase

The online calibration phase trains multiple context-aware radio maps from the labeled RSSI samples. One difficulty with online calibration is that collecting enough samples to train an accurate radio map may take several days or weeks. Based on our experiences with our training engine, training an accurate radio map in a 1000 $m^2$ space may need over 200 traces of RSSI samples. The number of traces required is proportional to the size of the environment – the larger the environment, the higher number of traces required. When environment factors are considered, even more RSSI samples are needed to train all possible context-aware radio maps, creating a **cold-start problem** – the system suffers from poor positional accuracy during initial deployment before context-aware radio maps have been trained with sufficient samples. This cold-start problem was solved by building a **cold-start radio map** trained with all RSSI samples from all environment conditions. If the system cannot find an accurate, context-aware radio map with sufficient training samples, then it refers back to the cold-start radio map to estimate locations.

Consider the following example. The environment is a 1000 $m^2$ space. The system adapts to the following three environment factors, people, doors and humidity. Each environment factor has two possible states. For people, these states are no-blocking or block-around; for doors, they are open or closed, and for humidity, they are high or low. These states combine to give a total of eight possible state combinations and eight context-aware radio maps corresponding to each environment state (for example, the set of no-blocking, open-doors, and high humidity is regarded as...
one state). The system initializes eight empty context-aware radio maps and one cold-start radio map. Given a trace of labeled samples, the online training engine looks up the environment label, and trains the corresponding context-aware radio map with the samples. The labeled samples are also applied to train the cold-start radio map.

3.3 Adaptive Localization Phase

When the adaptive location estimation engine receives RSSI values from a mobile device, it queries the environment sensors to obtain the current environment condition (people, doors and humidity), and then choose a radio map that best matches the current environment condition. If the best-matched radio map has too few training samples (i.e., less than 200 traces of samples), then the cold-start radio map is chosen, since it is likely to estimate more accurate positions. The chosen radio map can be applied to a location estimation engine to calculate the location of a target. The current implementation employs the location engine provided by ITRI [12]. However, the proposed architecture design defines interfaces to enable any (e.g., the best performing) location estimation engines to be plugged into the system.

During the online usage, the adaptive localization phase runs in parallel with the other two phases. When the location system receives RSSI values from a mobile device, both the localization phase and the sample collection phase are executed to run online calibration and online location estimation simultaneously.
Chapter 4

Sensor-Assisted Collaborative Localization

Collaborative localization leverages the variance in location accuracy among nodes within a cluster. Intuitively, nodes in the same cluster may help localize each other so as to enhance the overall average positional accuracy of the cluster. By identifying nodes with high location accuracy, we can use their location estimations to help better localize neighbor nodes with lower location accuracy. The design for collaborative localization is shown in Figure 4.1. It consists of the following three modules: Neighborhood Detection, Confidence Estimation, and Collaborative Error Correction. The general work flow of the system is summarized as follows.

1. **Neighborhood Detection** identifies nearby neighbor nodes as possible candidates for collaborative localization;

2. **Confidence Estimation** computes and attaches a *confidence score* to the position estimation returned by a given localization system (e.g., Ekahau). *Confidence* measures the probability of a location estimation being accurate,
3. **Collaborative Error Correction** adjusts the estimated location of the target node using the estimated locations of neighboring nodes with higher confidence scores. This way, the error in location estimation of the target node can be reduced.
4.1 Neighborhood Detection

For each target node, the Neighborhood Detection finds its neighbor nodes within 2 meters proximity radius. Each node periodically probes its neighborhood through a Zigbee proximity sensor, and the system continues to track the neighboring relationships among all target nodes.

4.2 Confidence Estimation

Confidence Estimation measures the probability of the location estimation, obtained from an underlying localization engine, being close to its true location. In other words, a high (low) confidence score implies that the location estimation has a high (low) probability of being the true location. Confidence in location estimation correlates highly to positional stability of a target node computed over time from a particle filter. Location estimation is based on the sensor model generated by a given localization engine, which is used in conjunction with a motion model to constrain location estimation within a reasonable variation consistent with human movement. That is, given the current location of a target, there is a limited range of possible locations that a human may reach. As a result, the difference between the location estimated from a sensor response $S$ and the bounded estimation $P$ returned from a particle filter implies the uncertainty in location estimation.

The confidence estimation can be derived by accumulating successive uncertainties over a specified time window. Specifically, we define the confidence at time $t$ according to the following equation:

$$Conf(t) = e^{-\frac{\left[\sum_{i=0}^{t} w(t) \cdot u_{c}(t-i)\right]^2}{k}}$$

(4.1)
Here, $t$ is the current time stamp, $i$ is an accumulation index, and $s$ is the length of the time window. Let $w(i)$ be the weight to accumulate uncertainties at different times within the window, and $uc(t-i)$ measure the uncertainty of a sensor response, i.e. the difference between the location estimation from the sensor response and the bounded estimation returned from a particle filter at time $(t-i)$. Equation 4.1 computes the weighted sum of uncertainties over an accumulation window $s$, normalizing it to a value between $[0,1]$. The value $k$ is a constant that adjusts the speed of decline in a logarithmic curve – a higher $k$ value means that the curve will decline more slowly. A high confidence score, e.g., 0.95, means that a particle filter has found little uncertainty over the time window, indicating high accuracy in location estimation. In the current implementation, $s$ is defined as the 3 most recent samples, constant $k$ is 300, and the weight $w(i)$ is equal for the three samples.

In order to validate how well Equation 4.1 models the relationship between confidence and accuracy of position estimations, we have conducted an experiment by collecting 1179 location estimation samples. These samples’ confidence scores are computed from Equation 4.1 and then plotted against their estimation errors from their true locations. Results in Figure 4.2 show a good inverse relationship between confidence and error.

### 4.3 Collaborative Error Correction

Collaboration Error Correction (CEC) enhances location estimation from particles of a target node by removing estimation that has a lower confidence score, from estimations of its neighbor nodes that have higher confidence scores.

Collaborative enhancement is based on the concept of attraction from magnetic interactions in nature. A high confidence node $N_x$, whose location estimation is at
CHAPTER 4. SENSOR-ASSISTED COLLABORATIVE LOCALIZATION

Figure 4.2: Confidence scores and location estimation errors

$N^\text{pos}_x$, is assigned a stronger magnetic charge $N^\text{conf}_x$. On the other hand, a low confidence neighbor node $N_y$, whose location estimation is at $N^\text{pos}_y$, is assigned a weaker magnetic charge $N^\text{conf}_y$. Based on natural magnetic interactions, a low confidence node, acting as a nail, will be pulled from its original position at $N^\text{pos}_y$ toward the position of a high confidence node at $N^\text{pos}_x$. The magnitude of this attraction force (refer to as the neighboring force) is proportional to the ratio $N^\text{conf}_x/N^\text{conf}_y$.

The actual mechanism can be described as follows. In step 1, for each node $N$, we collect its proximity nodes and $<$estimated location, confidence score$>$ pairs. In step 2, the neighboring force $F_b$ between a target node $N$ and one of its neighbor node $N_b$, is computed as follows:

$$F_b = \frac{N^\text{Conf}_b}{N^\text{Conf}_x + N^\text{Conf}_b} \times |D(N^\text{pos}_x, N^\text{pos}_b) - r \times (l + \varepsilon)| \times u(N^\text{pos}_x - N^\text{pos}_b) \quad (4.2)$$

Here, $r$ measures the proximity distance between the node pairs, $\varepsilon$ is a constant
measuring the amount of error ratio in a neighbor proximity measurement, $D$ is the Euclidean distance between two coordinates $N_{pos}$ (a target node’s position) and $N_{pos}^b$ (a neighbor node’s position), and the unit vector $u(N_{pos}^b - N_{pos})$ gives the direction of this neighboring force. In step 3, since a target node can have multiple neighbor nodes, individual attraction forces contributed from each of its neighbor nodes are summed into an aggregate neighboring force $F$, which is defined in equation 4.3. Note that $F$ is computed as a weighted sum of neighboring forces, with the weight equal to the normalized confidence level of each of its contributing neighbor nodes.

$$F = \sum_{b=1}^{s} \frac{N_{Conf}^b}{\sum_{i=1}^{s} N_{Conf}^i} \times F_b$$  \hspace{1cm} (4.3)

In the last step, we apply $F$ to correct the location estimation of a target node. This corrected location estimation is then used to assign probabilities of particles. Finally, the particle with the highest probability is chosen as location estimation.
Chapter 5

Experiments

The following three experiments were performed to evaluate the proposed adaptive indoor location system. In the first experiment, the RFID-assisted online calibration was evaluated based on constant-speed walking and in a static environment state (not considering environmental dynamics). The positional accuracy of the online and offline calibration was compared. In the second experiment, adaptive localization that utilizes online calibration to construct context-aware radio maps under changing environment dynamics was evaluated. The positional accuracy of adaptive and non-adaptive localization was compared under changing environment dynamics. In the third experiment, collaborative localization was evaluated under different levels of human clustering. The positional accuracy of collaborative and non-collaborative localization was compared under human clustering.
5.1 Performance Evaluation on RFID-assisted Online Calibration

To evaluate the performance of our online calibration without being affected by changing environmental factors, the environment state was left unchanged to ensure that only one person walks on the corridor in each time period. Figure 5.1 shows the layout of this experimental test-bed on the 3rd floor of our department building: the red triangles (▲) mark the locations of APs; the blue circles (○) mark the locations of RFID readers, and the shaded green lines mark the walking segments.

Three human subjects (graduate students) acted as testers in our experiments. Each subject carried a RFID-tagged PDA and walked along the shaded-lined segments, hitting four RFID readers in both clockwise and counter-clockwise directions. A data trace was denoted by RSSI values received by a subject through a walking segment from one RFID reader to the adjacent reader. A data unit was denoted as RSSI values when a subject walked two circles in the counter-clockwise and clock-
wise directions. This means that each data unit contains eight data traces. A total of 27 data units (216 data traces) were collected from three human subjects, and all are constant-speed walking. As each data trace is collected online, the system feeds it into the online training engine to refine our radio map, and simultaneously runs the location estimation engine to track the user’s position. The results in Figure 5.2 illustrate that the average positional accuracy improves as the number of data traces increases, converging to approximately 2.9 meters.

The performance of the manual offline calibration in the traditional Wi-Fi based methods is compared to our automated online calibration. For fair comparison, the same location estimation engine and site survey software are used to construct the radio map. The site survey selects 40 RSSI samples from each of 24 fixed sampled

![Graph](image)

Figure 5.2: Average positional accuracy with increasing training traces
5.2 Performance Evaluation on Adaptive Localization

A small area (approximately 400 m²) shown in Figure 1.1 was selected to perform the 2nd experiment. Since this small area is a closed space, it allows better control
and manipulation of the environment state, and then observes how well the adaptive localization adjusts to changing environmental dynamics. This small area had five APs depicted as triangles, deployed in 5 different rooms on a corridor. Two RFID readers depicted as circles were deployed at two endpoints of the corridor. The location system tracks a human subject carrying an RFID-tagged PDA and walking along the corridor. Multiple context-aware radio maps were constructed using the proposed online calibration method. To determine how well the proposed location system adapts to different changing environment factors, one environment factor state was altered at a time, and change in the positional accuracy was measured, also showing the effect of each individual environment factor on the positional accuracy.

5.2.1 Impact of Closed/Open Doors

The experimental setup was described to evaluate how well the proposed adaptive localization adjusts to doors while keeping unchanged the other environment factors (no-blocking people and 40% RH level). Additionally, to minimize the impact of other unforeseeable environment factors that may be time dependent, the experiment was conducted between 7 PM and 10 PM. The experiment consisted of the following three steps. In the Step 1, all doors were closed, and online calibration was then applied to train the close-all-doors radio map. In Step 2, all doors were opened, and online calibration was applied to train the open-all-doors radio map. In Step 3, the average positional accuracy was measured by applying each of two radio maps (closed-all-doors & open-all-doors) to each of the two environment conditions. There are four map-environment combinations between two radio maps and two closed/open doors environment conditions.

The average positional accuracy with increasing training samples of each of these four map-environment combinations is plotted in Figure 5.4. The cumulative dis-
distribution functions (CDF) are plotted in Figure 5.5. When the close-all-doors radio map is applied to estimate locations in the same close-all-doors environment, the average positional accuracy is 2.13 meters after 20 data traces. When the close-all-doors radio map is applied to estimate locations open-all-doors environment, the average positional accuracy (after 20 data traces) deteriorates by 5.04 meters to 7.17 meters. When the open-all-doors radio map is applied to estimate locations in the open-all-doors environment, the average positional accuracy is 2.81 meters after 20 data traces. When the open-all-doors radio map is applied to the close-all-doors environment, the average positional accuracy (after 20 data traces) deteriorates by 1.78 meters to 4.59 meters. Notably, under changing environment dynamics, the proposed adaptive localization can avoid applying the wrong radio map to the cur-

Figure 5.4: the impact of close/open doors on the average positioning errors with increasing training samples under different map-environment combinations
That is, the adaptive localization can achieve a good positional accuracy of 2.13–2.81 meters, while the non-adaptive method has a poor positional accuracy of 4.59–7.17 meters.

Table 5.1: Impact of Open/Close Doors on Average Positional Accuracy

<table>
<thead>
<tr>
<th>Average positional accuracy</th>
<th>Close-all-doors radio map</th>
<th>Open-all-doors radio map</th>
</tr>
</thead>
<tbody>
<tr>
<td>Close-all-doors environment</td>
<td>2.13 m</td>
<td>4.59 m</td>
</tr>
<tr>
<td>Open-all-doors environment</td>
<td>7.17 m</td>
<td>2.81 m</td>
</tr>
</tbody>
</table>
5.2.2 Impact of Relative Humidity

We evaluate how well the adaptive localization adjusts to varying relative humidity levels (RH) while leaving other environmental factors (close-all-doors and no-blocking people) unchanged. The experiment consisted of the following three steps. In Step 1, a dehumidifier was run to bring the RH in the environment down to 40%, and online calibration is then applied to train the 40%-RH radio map. In Step 2, the windows were opened to allow RH to reached 70%, and online calibration was applied to train the 70%-RH radio map. In Step 3, the average positional accuracy was measured by applying each of two radio maps (trained under 40% & 70% RH environments) to each of the two environmental conditions.

Figure 5.6: the impact of humidity (40% and 70% RH levels) on the average positioning errors with increasing training samples under different map-environment combinations
CHAPTER 5. EXPERIMENTS

The average positional accuracy with increasing training samples of each of the four map-environment combinations is plotted in Figure 5.6 and their cumulative distribution functions (CDF) are plotted in Figure 5.7. Table 5.2 summarizes the average positional accuracy. It also leads to the conclusion that adaptive method outperforms non-adaptive method.

Table 5.2: Impact of Humidity Levels on Average Positional Accuracy

<table>
<thead>
<tr>
<th>Average positional accuracy</th>
<th>40% RH radio map</th>
<th>70% RH radio map</th>
</tr>
</thead>
<tbody>
<tr>
<td>40% RH environment</td>
<td>2.13 m</td>
<td>3.68 m</td>
</tr>
<tr>
<td>70% RH environment</td>
<td>3.06 m</td>
<td>2.59 m</td>
</tr>
</tbody>
</table>
5.3. PERFORMANCE EVALUATION ON COLLABORATIVE LOCALIZATION

5.3 Performance Evaluation on Collaborative Localization

The third experiment was performed on the corridors of the 3rd floor of the Computer Science Department building in our university as shown in Figure 5.1. The baseline Wi-Fi positional engine is a commercial product Ekahau [5]. All users brought mobile devices equipped with the same brand IEEE 802.11g WLAN card. To evaluate performance of our collaborative localization, a scenario consisting of stationary people forming human clusters is shown in Figure 1.5. We then observe how well our collaborative localization can improve positional accuracy over the baseline Wi-Fi positional engine.

There are two cases of 3-person and 7-person stationary clusters with a cluster radius fixed to either 0.5 meter (called a dense cluster) or 1 meter (called a sparse cluster). The Figure 5.8 plots cumulative distribution functions (CDF) of average positional errors for 3-person dense and sparse clusters. Curves labeled "no-collaboration" show results when collaboration is not applied to location estimations, whereas curves labeled "collaboration" show results when collaboration is applied to location estimations. In addition, the curve labeled "3-person non-clustering" shows results when 3 stationary persons are standing apart without forming any cluster. This is used as a reference line for comparing with clustering cases. In the 3-person sparse cluster case, collaboration produces 37.2% accuracy improvement from 3.38 meters (no-collaboration) to 2.12 meters at 75% precision. Moreover, the average error is reduced by 34% from 2.41 meters to 1.59 meters. In the 3-person dense cluster case, collaboration produces 38% accuracy improvement from 5.38 meters (no-collaboration) to 3.34 meters at 75% precision. Moreover, the average error is reduced by 28.2% from 3.33 meters to 2.39 meters.
CHAPTER 5. EXPERIMENTS

Figure 5.8: CDFs of average positioning errors in the 3-person cluster scenario

The Figure 5.9 shows a positive relationship between the amount of accuracy improvement received by a target node, after applying collaboration, and $\Delta \text{Confidence}$, which is the difference in confidence scores between a target node and its neighbor node, in a 3-person dense cluster case. The plot shows that when $\Delta \text{Confidence}$ is positive (i.e., a neighbor node has a higher confidence score than a target node), collaboration can help improving positional accuracy of a target node. More importantly, a larger $\Delta \text{Confidence}$ results in a higher accuracy improvement, because a target node can benefit more from a neighbor node whose location estimation has a better accuracy than its location estimation. On the other hand, when $\Delta \text{Confidence}$ is negative (i.e., a neighbor node has a lower confidence score than a target node), collaboration is disabled because a neighbor node is likely to have worse positional accuracy than a target node.

The Figure 5.10 plots cumulative distribution functions (CDF) of average posi-
5.3. PERFORMANCE EVALUATION ON COLLABORATIVE LOCALIZATION

Figure 5.9: the amount of accuracy improvement versus the neighborhood confidence difference in the 3-person dense cluster

Figure 5.9: the amount of accuracy improvement versus the neighborhood confidence difference in the 3-person dense cluster

tional errors for 7-person dense and sparse clusters. Results show that the amount of accuracy improvement in 7-person clusters is greater than that of 3-person clusters. In the 7-person sparse cluster, collaboration produces 54.7% accuracy improvement from 6.26 meters (no-collaboration) to 2.83 meters at 75% precision. Moreover, the average error is reduced by 49% from 4.20 meters to 2.14 meters. In the 7-person dense cluster, collaboration produces 49.2% accuracy improvement from 7.25 meters (no-collaboration) to 3.68 meters at 75% precision. Moreover, the average error is reduced by 56.3% from 5.95 meters to 2.60 meters. Similar to the 3-person case, Figure 5.11 shows a positive relationship between the amount of accuracy improvement and the confidence difference with a neighbor node.
Figure 5.10: CDFs of average positioning errors in the 7-person cluster scenario

Figure 5.11: the amount of accuracy improvement versus the neighborhood confidence difference in the 7-person dense cluster
Chapter 6

Conclusions and Future Work

This work quantitatively measured how changing environmental dynamics adversely affects the positional accuracy in the Wi-Fi based location systems. To reduce this adverse effect, a new sensor-assisted adaptation method was proposed to adapt the localization engine to the current environment condition. The proposed adaptation method involves 4 phases: (1) the sensor-assisted sample collection phase applies sensor data from environment sensors to label RSSI samples with locations and environment condition; (2) the online calibration phase utilizes these labeled RSSI samples to construct multiple context-aware radio maps, (3) the adaptive localization phase chooses a radio map that best matches the current environment condition for location estimation, and (4) the sensor-assisted collaborative method leverages location estimations from neighbor users that have higher location accuracy to enhance the location estimation accuracy of human cluster.

Experiments tested three dynamic factors: doors, humidity, and human clusters, which change frequently in the evaluated environment. Humidity sensors, pressure sensors (already existed on the security control doors), and Zigbee proximity sensors (for detecting nearby people) were used to detect changes in these dynamic factors.
Our experimental results have shown that, in comparison to traditional localization methods, the proposed enhancement can avert the adverse effect on the positional accuracy: 5.04 meters by detecting open/closed doors, 0.93 meter by sensing humidity level, and 50% accuracy improvement in human clustering cases by applying collaboration. The experimental results also show that our automated online calibration can create radio maps that are almost as accurate (off by a small 0.17 meter in positional accuracy) as those from traditional offline calibration.

The proposed systems have several limitations. Our experiments were performed mainly in the corridor, rather than within rooms. Additional RFID readers may need to be installed inside rooms to enable automatic online calibration. This requirement may add cost to the sensor part of this localization system. However, we believe that future environments will have richer sensor infrastructure shared and reused by many context-aware applications, including our localization systems.

Our future work will attempt to discover additional environment factors that can occur frequently and affect positional accuracy. We would also like to explore additional sensors that can detect environment factors and help further improve the positional accuracy. In the opposite direction, environmental factors could be detected without using sensors. For example, opening and closing doors may be detectable by observing unique RSSI patterns across multiple mobile client devices. When a door is closed with an access point inside, mobile client devices outside that room should observe a significant drop in RSSI from that access point, thus exposing the status of the door.
Appendix A

Yi-Chao Chen’s Publications


Bibliography


