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室內及室外環境下之 GSM/Wi-Fi 定位系統分析比較

Performance Comparison between GSM and Wi-Fi Localization in both Indoor and Outdoor Environments

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中文摘要

定位系統已被廣泛地應用在各種服務，一旦系統得知人以及物件的位置，服務的種類將可變地更為個性化，這些與位置相關的服務包括導航、地域性的廣告、後勤服務、庫存管控、以及博物館導覽等等，而用來啟動及推廣這類服務的，會是一套可於任何時刻在室內及室外環境下精準定位人及物件的系統。

為了實際地評估建立一個能廣泛覆蓋室內和室外環境的定位系統的可行性，我們選擇目前相當普及的 GSM 和 Wi-Fi 兩個無線網路，將利用這兩個無線網路所構成的定位系統放置到 Smart phone 和 PDA phone 上實現，並且在室內及室外環境〔例如：辦公室、都市、校園和郊區〕根據不同演算法〔Centroid、Weighted Centroid、及 Fingerprinting〕比較它們的定位表現。結果顯示基于 GSM 的定位系統的平均定位誤差在室內〔室外〕的環境下是11〔113〕公尺，基于 Wi-Fi 的定位系統在室內(室外)環境下的平均定位誤差為5〔29〕公尺，我們認為以這樣的精準度來建構一個可適用於室內及室外的定位系統是可行的。在實驗的過程中，我們討論遇到的幾個實際問題並且比較每種定位方法的優缺點。 在文章的最後，我們提出結合GSM及Wi-Fi兩種網路的混合式定位系統。

關鍵詞：GSM 定位、Wi-Fi 定位、室內室外定位、定位系統比較分析、混合式定位系統

Abstract

Location is considered as one of most widely utilized context information in context-aware computing. Location-aware services leverage the location of people and objects to provide relevant or personalized information and services to users. An enabling technology is a ubiquitous (pervasive) location system that can accurately track positions of people and objects anytime anywhere in both indoor and outdoor environments. Examples of these location-aware services include navigation services, location-based advertisement services, logistical services, inventory control services, museum guide services, etc.

To evaluate feasibility of constructing a practical localization system, which can have wide coverage in both the indoor and outdoor environments, we have selected GSM and Wi-Fi based localization systems, implemented them on commercial GSM/Wi-Fi smart phones and PDAs, and compared their performance under different positioning algorithms (e.g., centroid, weighted centroid, and fingerprinting) and different indoor/outdoor environments (e.g., offices, urban and rural areas). Results have shown that the average positional accuracy of a GSM based localization in indoor(outdoor) environment is 11(113) meters, and the average positional accuracy of a Wi-Fi based localization system in indoor(outdoor) environment is 5(29) meters. We consider the accuracy feasible and sufficient for an indoor/outdoor localization system. From our deployment experiences, we discuss several practical problems encountered and compare the pros and cons of each localization method. Finally, we propose a GSM/Wi-Fi hybrid localization system that combines the advantages of both GSM/Wi-Fi localization systems.

Keywords: GSM Localization, Wi-Fi Localization, Localization performance comparison, indoor/outdoor Localization, Hybrid Localization System

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Chapter 1
Introduction

1.1 Location System

Location system is one of the key technology building blocks for ubiquitous computing systems and applications. The “where” context, i.e., person/object's location, has been shown to be one of the most widely-used and easily-accessible context in making smart objects and smart environments for the research of ubiquitous computing or context-aware computing [1, 2]. Examples of these applications at home include home automation, home security systems, elders’ activity recognition, object tracker, etc.

From the system point of view, positioning technologies can be classified into network based and mobile station based localization. Network based localization takes advantage of network deployment and it obtains an object’s position by coordinating its network facilities or via its synchronous signals. Since the estimation of an object’s location is processed in the core networks, more complex algorithms can be applied to the system and the design of a mobile device can be made as simple and power efficient as possible. However, the network based method may locate a user with or without his/her awareness and consent, it has a danger of potentially infringing on a user’s privacy. Mobile station based localization uses mobile devices’ processing capability to calculate its own position by observing and analyzing ambient radio beacons. In the mobile based location, a mobile device needs to a sufficient storage capacity of a positioning database and a processing capacity to compute its position in or near real time. Therefore, this raises the issues of computing resource and battery life on mobile devices.

The current most popular location system is the GPS system. The GPS system requires using a GPS receiver that has a clear line-of-sight to GPS satellites flying over the sky. This means that GPS system (without any additional infrastructure supporting indoor operations) is limited to the outdoor environments. Studies have shown that average people nowadays spend more than 90% of their times in the indoor environments. This significantly reduces the availability of the outdoor GPS system, and raises a demand for indoor location systems. In the past few years, we have seen a large number of research developments in indoor location systems that tries a variety of methods [3], such as matching fingerprints of Wi-Fi, GSM, and Zigbee radio signal strength [6, 13-15, 22-28,], calculating distance from ultrasonic or infrared signal's time-of-flight [4, 5, 32], vision tracking from multiple cameras[9, 10], active/passive RFID signaling the nearest known-location positioning nodes [18, 29-31], detecting phase difference in ultra wide-band (UWB) pulse signals [17], location-sensing floors [12], and many others.

However, we have seen very limited number of successful examples of localization system to operate in both indoor and outdoor environments. Why is that? Based on our experiences, we have identified three practical deployment barriers that have not been successfully overcome "as a whole" by existing location systems: positional accuracy, infrastructural coverage, and infrastructural stability. Positional accuracy is about reducing error in pinpointing the spatial position of a target. Infrastructural coverage is about the availability of reference signals in the environment that can be used by the localization systems. This has to do with the cost of infrastructural deployment that can scale up to wide indoor and outdoor environments. Infrastructural stability is about the maintainability and stability of the infrastructural components. An unstable infrastructure would affect the accuracy and increase the cost of calibration. A practical localization system should ideally provide good positional accuracy (therefore can satisfy the accuracy requirements of many applications), wide indoor and outdoor coverage, (therefore can provide a good accuracy), and good infrastructural stability (therefore can reduce the cost of calibration). More importantly, it should be able to work in both indoor and outdoor environments.

1.2 GSM and Wi-Fi

GPS is considered one of the most well known location technologies. GSM or emerging 3G (UMTS/CDMA2000) networks are also important because of their pervasive coverage in both indoor and outdoor environment. In recent years, Wi-Fi network has also become almost in-par with cellular network, in popularity and coverage in dense urban areas, as the need for high-speed wireless communication increases and attractive cost.

Since GPS has a roof limitation and we are in the indoor environments more than 90% of time, we are evaluating alternative radio mediums that can operate both indoor and outdoor in NLOS (non line of sight) mode. Two kinds of radio signals are considered in this thesis work, GSM and Wi-Fi, due to their ubiquitous coverage in modern lives. The GSM (Global System for Mobile Communications) is the most popular standard for mobile phones in the world. Its service is currently used by over 2 billion people across more than 212 countries and territories. The ubiquity and pervasive existence of the GSM standard makes international roaming very common between mobile phone operators, enabling subscribers to use their phones in many parts of the world. Wi-Fi shares many similar characteristics as GSM. Wi-Fi is a brand to describe the underlying technology of wireless local area networks (WLAN) based on the IEEE 802.11 specifications. Originally, it was designed to be used for mobile computing devices to constitute LANs, but is now increasingly used for broad digital services, including Internet and data access, online gaming and connectivity of consumer electronics or intelligent appliances. Recently, the standard of WiMAX (IEEE 802.16) has been mature, and it is likely to be the candidate solution of "last mile" wireless broadband access. Due to the regulations of radio spectrum and the rare infrastructural availability, compared with Wi-Fi, WiMAX is not as popular as Wi-Fi nowadays. But it is likely to be pervasive given its broader bandwidth and wider coverage in design.

In Taipei, the City's wireless network has named the largest and densest Wi-Fi network in the world [36]. That means we can gain access to Wi-Fi signals in almost all indoor and outdoor spaces in Taipei City; therefore, it has become an attractive testbed for deploying Wi-Fi localization system.

In our work, we practically deploy our localization systems on commercial GSM-Wi-Fi hybrid smart phones and compare the performance between GSM and Wi-Fi systems. We have implemented different positioning algorithms including Basic Centroid, Weighted Centroid, and Fingerprinting, and conducted real experiments to evaluate and compare their performance.

From our experimental results, using the same positioning algorithm, Wi-Fi based location systems can achieve almost one order of magnitude better positional accuracy and precision than GSM based location systems. In addition, we recommend the Centroid algorithm in the outdoor environment, because of its low training cost and relatively low computing power. Note that since outdoor environments usually cover large areas, we have to collect lots of data before the tracking phase can take place. Due to limited CPU and storage resources on a mobile device, it is necessary to adopt a light-weight algorithm for training and tracking. The Fingerprinting algorithm is recommended in the indoor environment because indoor applications tend to require more positional accuracy and precision. Better accuracy can be achieved by a deliberately and densely trained Fingerprinting system. These are our recommendations given today's technologies. However, in the future, a mobile device may have much more computing and storage capabilities that our recommendations may not apply.

Fig. 1. Outdoor activities

1.3 Research Claim

This is a feasibility study of localization systems that utilize ubiquitous GSM and Wi-Fi radio signals to provide wide area coverage and both in the indoor and outdoor environments. To claim their feasibility, we have prototyped working localization systems on GSM/Wi-Fi hybrid mobile devices and conducted experiments to measure their performance in positional accuracy. Our experimental results show that Wi-Fi(GSM) localization systems can achieve an average positional accuracy in the range of 11(113) meters in the outdoor environment and 5(29) meters in the indoor environments. We believe that the positional accuracy is sufficient to enable some indoor/outdoor location-aware services.

1.4 Thesis Organization

The remainder of this thesis is organized as follows. Chapter 2 describes related work. Chapter 3 presents different positioning algorithms including centroid, weighted centroid, and fingerprinting. Chapter 4 provides details of our implementation of these positioning algorithms using GSM-Wi-Fi hybrid smart mobile devices. Chapter 5 discusses our experimental results. Chapter 6 proposes a hybrid method that combines both GSM and Wi-Fi localization, followed by conclusions and future works in Chapter 7.

Chapter 2
Related Work

There is a large amount of related work literature on localization systems. We can group these systems under four general categories: (1) radio signal strength (RSS) based systems, (2) acoustic based systems, (3) infrared based systems, and (4) RFID based systems. We will discuss them in details and point out their limitations.

The first category is based on using radio signal strength (RSS). RSS based methods can be applied on different radio technologies. In general RSS based systems are based on the fingerprinting algorithm, which is consisted of two general phases. The first phase is called calibration phase, in which a radio map is manually constructed by moving about different location points in the deployed environment and recording their radio signal strength in the radio map. The second phase is positioning phase, in which RSS values from mobile devices are compared to the recorded values on the radio map to infer the devices' current positions. Given the ubiquity of Wi-Fi access points in city and suburb areas, the most popular RSS method is using Wi-Fi signals. These Wi-Fi systems can be categorized into two broad approaches. The first approach is based on the deterministic method [6, 22]. 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 [6] applies KNN to obtain the k nearest neighbors, where a neighbor is a sampled point on the radio map, and nearness is denoted 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 [23, 24, 25, 26]. For example, Seshadri et al. [26] 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. One of the most successful commercial Wi-Fi localization system Ekahau [22], claims that it can achieve positional accuracy to 2~3 meters. Since we have also purchased and deployed the Ekahau system, our testing shows that such 2~3 meters average accuracy is only attainable for stationary objects in ideal environments, but not applicable to moving objects and general indoor environments.

Several research teams have tried using GSM radio fingerprinting [13, 27, 28] for indoor & outdoor localization. These research projects are similar to our work. Their reported positional accuracy numbers varies: the University of Toronto team [13] reported indoor positional accuracy of 5 meters in large multi-floor buildings. However, we have performed similar experiments using GSM signals in our department buildings, and our accuracy results are doubled (in tens of meters) than their reported results. Though the method to use channelID, suggested in their work, can provide a higher accuracy, it is not practical when deploying such systems at a large scale because of channel reuse in GSM networks and when the training and tracking are performed with different operator networks. Intel Research Seattle [27, 28] has also tested outdoor localization using GSM signals in Seattle, and their reported accuracy numbers are within one hundred meters, which are more inline with our testing. Our work has also conducted a similar feasibility and performance study using GSM/Wi-Fi radio signals in Taipei city, with a different Wi-Fi AP and GSM BS density.

Radio fingerprinting using Zigbee radios, due to its low power consumption, has also gained recent popularity recently. [14] uses Zigbee radio fingerprinting to leverage the lower power consumption of Zigbee radios. In comparison to Wi-Fi radio fingerprinting, the Zigbee radio fingerprinting can achieve much more stable location (i.e., with a much smaller variance); however, this comes with a high density of Zigbee sensor nodes in the environment. In addition, Zigbee is not as popular as Wi-Fi that the radio source is not commonly available. The positional accuracy is also highly affected by the changing conditions in the deployment environments (e.g., changing humidity level, presence of people, open and closed doors, etc.) [15], as well as the mobility level of tracked targets. Finally, RSS based systems require extensive manual calibration efforts to construct accurate radio maps.

The second category is using acoustic (ultrasonic) sensors, such as Active Bat [4] from AT&T research lab, Cricket from MIT [5], Dolphin from University of Tokyo [32], and many others. These systems are based on ultrasonic signal time-of-flight measurement to estimate distances to certain fixed positions in the environment and to apply the triangulation method to compute spatial coordinates. For example, Active Bat system [4] requires installing ultrasonic receivers in the environment and an ultrasonic transmitter on a mobile bat unit worn by each user. The Cricket system [5] reverses this setting by having ultrasonic receiver on the mobile user and the transmitters in the environment. This better protects the location privacy of the person. Synchronization among transmitters and receivers is done through radio signals, which travel much faster than ultrasonic signals. Although these ultrasonic systems can achieve good positional accuracy (in centimeter range), they have several known limitations, such as light of sight between beacon and receiver nodes, directionality of ultrasonic sensors, and limited range of ultrasonic signals. These limitations confine ultrasonic systems to narrow application domains.

The third category is based on infrared sensors, such as the Active Badge [8] system from Olivetti lab. Given that infrared travels at the speed of light, the Active Badge system requires a high precision synchronization protocol running over a dedicated wireline network infrastructure connecting all the infrastructure nodes. This wireline synchronization network hardware adds to the cost of its location systems and limits its scalability to a large area. Although these infrared systems can achieve centimeter positional accuracy, infrared signals are limited in relatively short range and severely affected by the presence of sunlight.

Given the readily availability and cost effectiveness of RFID technology, several recent studies [18, 29, 30, 31] have proposed using RFID to track locations. In general, these systems work based on proximity of RFID tags signaling the nearest RFID positioning node or RFID readers. Therefore, the locations of the RFID tags are the room locations of their nearby positioning nodes. The advantage of the RFID based systems are low (or no) energy consumption on the mobile badges. Unless a high density of these RFID sensors are deployed in the environment, these systems can achieve room-based accuracy in room-based environments; therefore, they are not suitable for open-space environments. Willis et al. [18] attached passive RFID tags with known locations to the carpet pads, and RFID readers in the shoes to read locations of these passive RFID tags. To reduce the manual efforts of deploying tags, Haehnel et al. [29] used a robot to explore and localize the RFID tags in the space. The LANDMARC system [30] placed active RFID tags on the objects and RFID readers in the environment to track the tags. The GETA Sandals [31] are a footprint-based location system that tracks user locations by embedding ultrasonic sensors and RFID readers inside the sandals.

Our work in this thesis aims to evaluate the feasibility of localization systems to fit in both indoor and outdoor environment. It is mostly based on RSS method. We collect RSSI in both Fingerprinting and Weighted Centroid localizations. In basic Centroid algorithm, we collect beacon addresses and estimate the location of a mobile device by calculating the arithmetic mean from all available beacons. All of the three localization algorithms are run on commercial cellular phones. We then compare GSM and Wi-Fi performance in both indoor and outdoor environments in several metrics and discuss the feasibility of these localization systems.

Chapter 3
Positioning Algorithms

Three kinds of positioning algorithms are adopted to compare the GSM/Wi-Fi localization systems in this work. They are (1) Centroid, (2) Weighted Centroid, and (3) Fingerprinting. We will describe these positioning algorithms in the following subsections.

3.1 Centroid Algorithm

Centroid localization [7] method assumes that the location of each beacon is a prior knowledge of the system. It involves two phases – the training phase and the tracking phase. In the training phase, the system collects all beacon coordinates and stores them in a database that will be used later during the tracking stage. The training phase involves walking or driving around the target area, and scanning all available beacons while recording their GPS coordinate at the same time. A beacon location is determined by calculating the arithmetic mean of all scans in which this beacon was detected. After the training phase, we generate a radio beacon list, comprising beacon ID and its GPS coordinate.

During the tracking phase, the mobile device detects all available beacons, finds the corresponding beacons' coordinates on a radio map, and then calculates the arithmetic mean of those beacons coordinates as its positional estimation. Figure 2 gives an example for Centroid algorithm. Assuming a person stands in location (A',B') and the device observes 6 beacons ((A1,B2), (A2,B2), ..., (A6,B6)) nearby, the Centroid algorithm will add all the available X axes and Y axes and divide it by 6, which is the number of observed beacons.

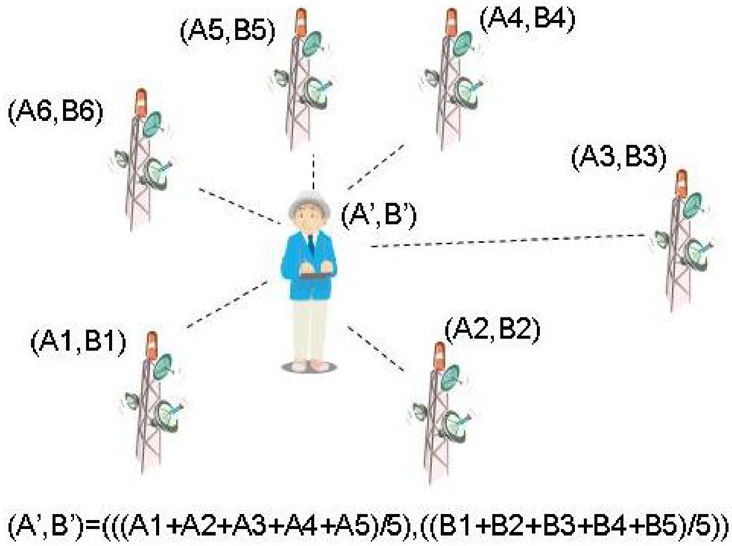

Fig. 2. Centroid Positioning (the coordinate of beacons is a prior knowledge)

2.2 Weighted Centroid Algorithm

The Weighted Centroid algorithm is an extension of the basic Centroid algorithm. As its name implies, a weight is added to each beacon according to this beacon's perceived signal strength. Since the Weighted Centroid relies on the relative RSSI of each beacon, it is not suitable to mix different radio sources in this method. For example: -70dbm in GSM may have a different weight than -70dbm in Wi-Fi. Based on our experiences, Weighted Centroid can provide a better positional accuracy in general while only slightly increasing the computational load.

Both Centroid and Weighted Centroid algorithms do not need to model the radio propagation. Furthermore, if the telecom operators who have the beacons coordinates in their network plan are willing to share such information, we can reduce a great effort in the training stage to find the beacons' coordinates. Since Centroid and Weighted Centroid adopt simple arithmetic calculation, they require less computing power in comparison with the Fingerprinting method. Note that in addition to positional accuracy, power consumption is also considered as a critical factor for a mobile device.

Figure 3 gives an example for Weighted Centroid algorithm. Similar to the Centroid algorithm, the location (A',B') is obtained by introducing a weighted parameter during mathematical operation.

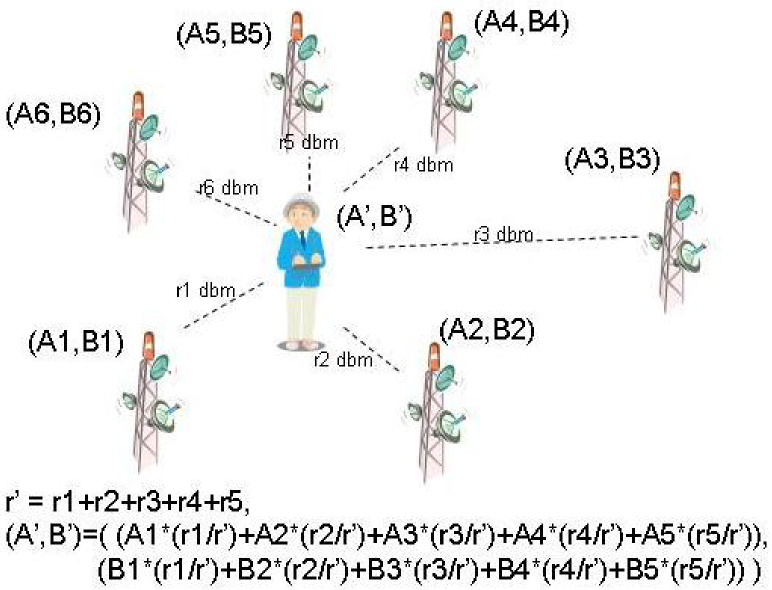

Fig. 3. Weighted Centroid Positioning

2.3 Fingerprinting

Fingerprinting is a method to collect radio fingerprints in a specific area and constitute a radio map as the training result. In tracking stage, it compares current RSSI fingerprints with the radio map, and finds the best matched location as its estimation.

In our experiments, we construct a fingerprint database with grid size of 10x10 meters in the outdoor environments and 2x2 meters in the indoor environments. Fingerprinting method may require more storage space because it has to collect as many radio fingerprints as possible for better accuracy. For an area like Hsin-Yi District in Taipei, the size of database is more than 4Mbytes. Since the system need to search each grid on the radio map to find best matches, the response time of the mobile device would go down as the size of database increases.

There are two ways to collect RSSI (Radio Signal Strength Indication) fingerprints in our training stage. One of both, like RADAR [6], plans several grids in a specific area; collect an amount of radio fingerprints in a static point, and save the arithmetic mean of perceived data to that grid. The database of radio map is formed after finishing all the training works. The other way does not pre-define a fixed grid size, but leave it to normal walking or driving speed. It records every scan of observed RSSI fingerprints as a single grid and combines all the grids as a radio map. Thus, people can drive or walk along the road or hallway without staying in a static point for a certain amount of time for Fingerprinting training. The second method is quite efficient when the radio source is stable, but offers a relatively low accuracy. Furthermore, it will result in a larger size of radio map.

The accuracy of Fingerprinting localization can be improved by apply additional models to the search. In this work, we use KNN (K=3) to filter out the noises during tracking stage.

Generally speaking, Fingerprinting positioning may take a longer time in training and take additional efforts in calibration as radio fingerprints or the infrastructure might change over time. For example: If a new building appears after we trained the radio map, we need to re-train the surrounding grids for calibration. But with Centroid algorithm, we do not have to change a thing. The Fingerprinting method consumes more processor resources than Centroid on the mobile device because the location estimation time is O(N), while Centroid takes O(1). Therefore, it is relatively not suitable for the applications in mobile devices, especially when the training area is large.

Finger 4 illustrates the operation of Fingerprinting algorithm. The localization system will compare its current RSSI fingerprints with radio map and finds the best match, G45, as its estimation.

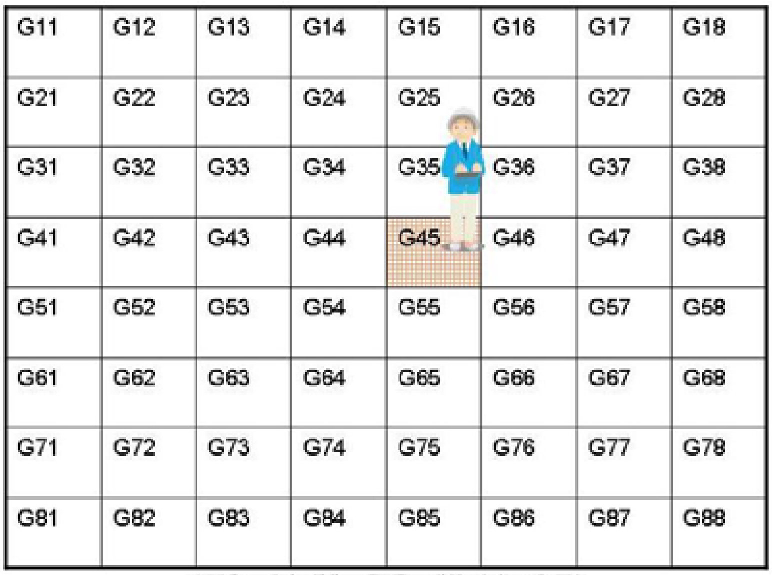

Fig. 4. Fingerprinting Positioning (find the best match among the grids)

Chapter 4
Implementation

In order to produce a practical result for the comparison between GSM and Wi-Fi localization, we prototyped working systems on commercial available smart phones with both GSM and Wi-Fi radio access. Since our smart phone can provide only one GSM operator's signal at a time, we use the Chung-Hwa Telecom's SIM (Subscriber Identification Module) card as it is the largest telecom operator in Taiwan. The CHT GSM operates on both 900MHz and 1800MHz frequency bands.

4.1Mobile Devices

Our smart phones are Dopod 585, Dopod 586w, and Dopod 900 [19]. They are produced by HTC, a Taiwanese company, and may have other names in different countries. The type of GPS module is Leadtek 9559x which provides GPS coordinates via Bluetooth connection.

On the software side, Dopod 585 runs the Windows Mobile 2003 SmartPhone Edition, Dopod 586W runs the Windows Mobile 5.0 SmartPhone Edition, and Dopod 900 runs the Windows Mobile 5.0 Pocket PC Edition. All of them are commercially available Smartphones or Pocket PC phones. Dopod 586W and 900 are additionally equipped with Wi-Fi radio access. We have chosen the Windows Mobile platform because of its easy development environment provided by Microsoft Visual Studio 2005 and it is convenient to deploy a user's program to the phones and debug the system during run time.

Since these smart phones are not equipped with a GPS module by default, we have utilized an external Bluetooth GPS receiver in our experiments. We assume that GPS coordinates are ground truth.

Fig. 5. The cellular phones and GPS receiver used for the research

4.2 System Architecture

Thank to Intel Research's open source project POLS [16], we save a lot of time by using parts of their project codes while reading GSM and Wi-Fi signals from smart phones. With the help of POLS, we can focus our efforts on implementing specific localization programs in our work. The system architecture is depicted in Figure 6.

Most of our software programs are written in Microsoft Visual C#, with some in C as external libraries. For the outdoor localization system, we have combined our system with a GIS map software, provided by Mactiontech's PaPaDO!SDK [20], which supports Microsoft SmartPhone 2003 edition. All the software programs can be deployed on the smart phones mentioned above.

Our system is consisted of the following five components:

Centroid / Weighted Centroid training program: it collects and calculates beacons' coordinates and store them in a beacon database. This database can then be applied to both basic and weighted Centroid algorithms.

Centroid / Weighted Centroid tracking program: it reads beacon ID and RSSI information, and calculates the location estimation by basic Centroid or weighted Centroid algorithms. We further compare the estimated position with actual coordinates, observed by the GPS module. Thus we can have detailed error distances during experiments.

Fingerprinting training program: it collects a specified amount of RSSI fingerprints on static grid points, calculates the average RSSI, records the (x,y) position on the map (indoor) or GPS coordinate (outdoor), and saves them on a fingerprinting radio map. The number of RSSI collections in a static grid can be adjusted according to the characteristics of the calibrated environments. For example, in an office environment, we may be able to collect 20 RSSI fingerprints and calculate the arithmetic mean on the grid. However, when driving along the streets, it is impossible to stay on any static points for long enough to collect 20 RSSI fingerprints..

Fingerprinting tracking program: it observes RSSI fingerprints, and finds the most similar grid from the radio map. Some motion models can be applied to the system in this tracking stage. However, we only applied simple filtering to remove the outliers produced by the KNN method. In the indoor environment, we calculated the error distances by measuring the Euclidean distance from the estimated position to the ground-truth position. In the outdoor environment, we assume that ground truth locations are GPS coordinated from the GPS modem.

Error calculation: it reads the current GPS location and compares it with the estimated position provided by GSM/Wi-Fi localization system. The results are then output to a excel file for further analysis.

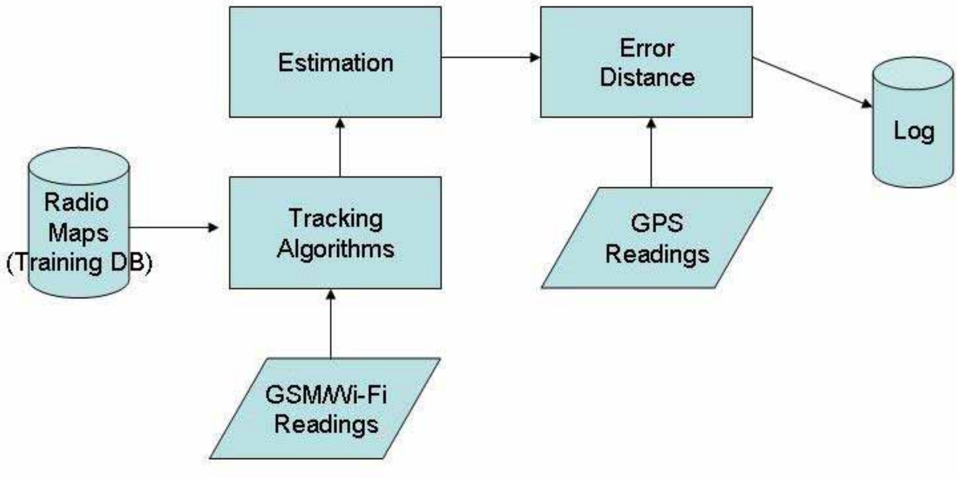

Fig. 6. System Architecture (Tracking)

4.2 GSM Implementation

Like most commercial cellular phones, our mobile device vendor does not expose standard APIs for reading GSM modem data to the user level program. As a result, we exploited a known hack that reads GSM modem output data left on certain memory address on the smart phone in the system, and then interprets such GSM modem data to valid cell information. We implemented the GSM RSSI reading functions as an independent task which provides RSSI information to the main task every second. The main program can then receive and update the positional estimation as the same rate as the GSM reading task. Using this hack, both Cell ID and Channel ID can be read and sent to the localization programs. Normally 6~7 cell IDs and 15~18 channel IDs can be read from the Dopod GSM modem. The number of accessible IDs is highly depending on the mobile devices. In general, the more IDs accessible the higher accuracy the system can provide. The GSM reading flows in our system is depicted in Figure 7.

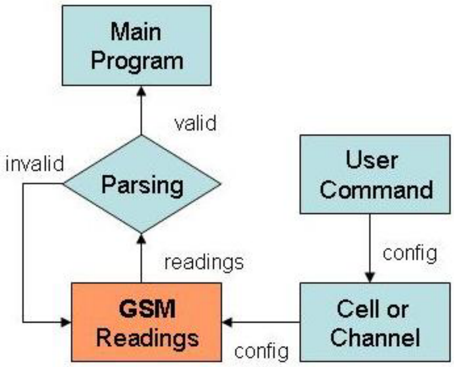

Fig. 7. GSM Implementation Diagram

4.3 Wi-Fi Implementation

Wi-Fi RSSI information is accessible from the device IO APIs provided by the Windows Mobile 5.0. Similar to the GSM reading functions, we implemented Wi-Fi readings in an independent task which sends its readings to the main task every second. The MAC address and SSID are read, together with RSSI (in dBm), in this task. Since Wi-Fi signal information is provided in standard APIs, a mobile device can obtain almost all actually nearby Wi-Fi access points from the device IO APIs. The Wi-Fi RSSI reading flows in our system is depicted in Figure 8.

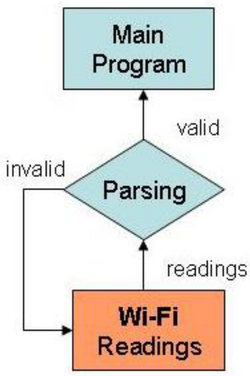

Fig. 8. Wi-Fi Implementation Diagram

4.4 Test Environments

We would like to conduct real experiences in different indoor and outdoor environments to evaluate the performance of GSM and Wi-Fi implementation. In Taiwan, GSM network deployment is available in almost all road accessible areas. Wi-Fi signals are available in most places in Taipei city as it claims to be the largest Wi-Fi city in the world [41].

In the outdoor experiments, three types of environments are selected to evaluate our implementation. They are (1) urban, (2) rural, and (3) campus. Hsin-Yi District in Taipei City, is selected as the urban area where it is a place with lots of commercial activities. It is supposed to have more GSM cellular towers than other non-commercial areas. Based on our measurements, within this 2 km^2 area, GSM cellular tower density is 27 cells per km^2, whereas the Wi-Fi AP (Access Point) density is around 500APs per km^2. In the area, we observed stronger GSM RSSI in average than other places. The rural area, Long-Tan village, in Tao-Yuen County, is a small area of 1 km^2. The cellular tower density is 9 cells / km^2 and Wi-Fi AP density is 77APs / km^2 In NTU (National Taiwan University) main campus, where it is a place of 1 km^2, the GSM cellular tower density is 20 cells / km^2, AP density is around 800APs / km^2.

In the indoor experiments, we have chosen the 3rd floor at NTU CSIE building as our testbed. From our experiments, we can observe around 5~6 GSM cellular towers and 18~20 Wi-Fi access points.

4.5 Error distance

Error distance is the result that we need to record while comparing accuracy with different localization methods and under different environments. In indoor experiments, we have the error distances by measuring the differences between estimated location and real location. In outdoor experiments, GPS is used as the ground truth. We generate beacon location database by recording beacon ID and RSSI fingerprints, together with GPS coordinates in training stage. In tracking stage, we calculate an object's estimated location, noted by GPS coordinates, and compare it with observed GPS coordinates at run time. The outdoor distance is calculated by Great Circle Distance Formula:

$$\Delta\sigma = \arctan\left\{ \frac{\sqrt{[\cos\Phi_2 \sin\Delta\lambda]^2 + [\cos\Phi_1 \sin\Phi_2 - \sin\Phi_1 \cos\Phi_2 \cos\Delta\lambda]^2}}{\sin\Phi_1 \sin\Phi_2 + \cos\Phi_1 \cos\Phi_2 \cos\Delta\lambda} \right\}$$

Let (Φ_1, λ_1), (Φ_2, λ_2) be the latitude and longitude of two points, respectively, $\Delta\lambda$ be the longitude difference and $\Delta\sigma$ be the angular difference/distance. If r is the radius of the sphere, then the great-circle distance is r$\Delta\sigma$.

Chapter 5
Experimental Results

Four experimental settings were chosen, namely urban, rural/residential area, NTU main campus and office (NTU CSIE building). Only the Fingerprinting algorithm was tested inside the CSIE building, since the beacon coordinates could not be determined without using a GPS. In other experimental settings, all three positioning algorithms (Centroid, Weighted Centroid, and Fingerprinting) were employed for comparison between GSM and Wi-Fi localization systems.

5.1 Precision and Accuracy

5.1.1 Urban Area

For an urban area, the Hsin-Yi District of Taipei was chosen as the testbed. Hsin-Yi District encompasses an area of 2 km^2, and is one of the busiest commercial areas in Taipei City, making it likely to have many GSM cellular towers and dense Wi-Fi access point distribution. The data training stage identified 27 cellular towers and 497 Wi-Fi APs in the area. Figure 9 shows the distribution of GSM and Wi-Fi beacons in Hsin-Yi District.

Fig. 9. GSM (Left) and Wi-Fi AP (Right) Distributions in Hsin-Yi District.

The average error of location estimation obtained by the Centroid localization method, was found to be 245 meters, whereas that obtained by Weighted Centroid was 161 meters. The average error of location estimation for Wi-Fi was 64 meters, whereas the Weighted Centroid was 84 meters.

Figure 10 plots the CDF (Cumulative Distribution Function) of the Centroid testing results Figure 11 plots the CDF of the Weighted Centroid testing results, and Fig. 12 plots the CDF of Fingerprinting results in Hsin-Yi District.

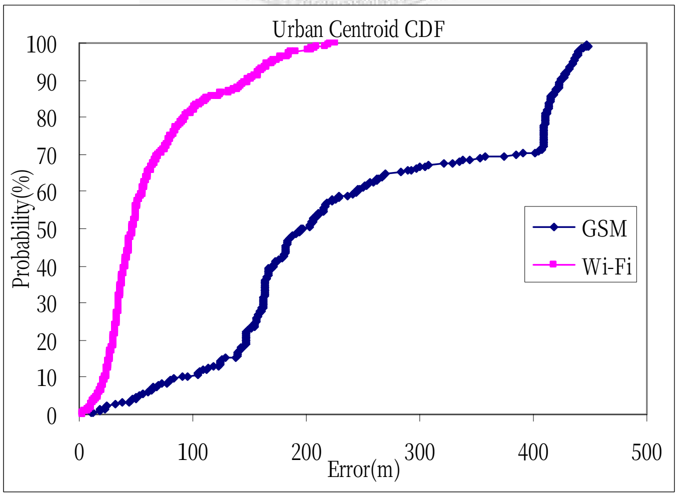

Fig. 10. CDF of GSM and Wi-Fi with Centroid Algorithm in urban area

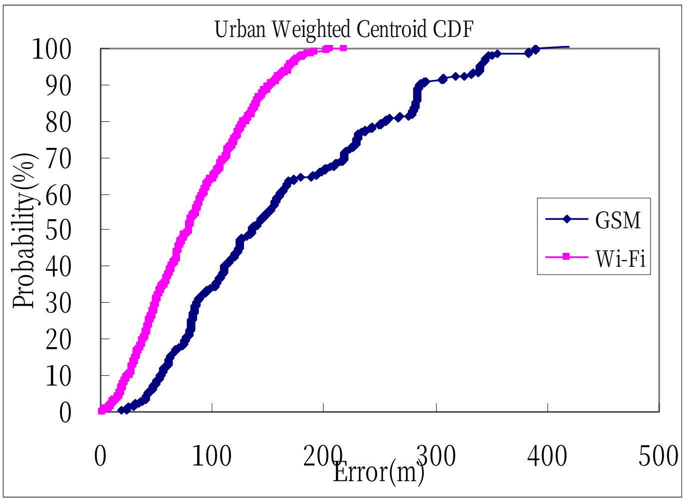

Fig. 11. CDF of GSM and Wi-Fi with Weighted Centroid Algorithm in urban area

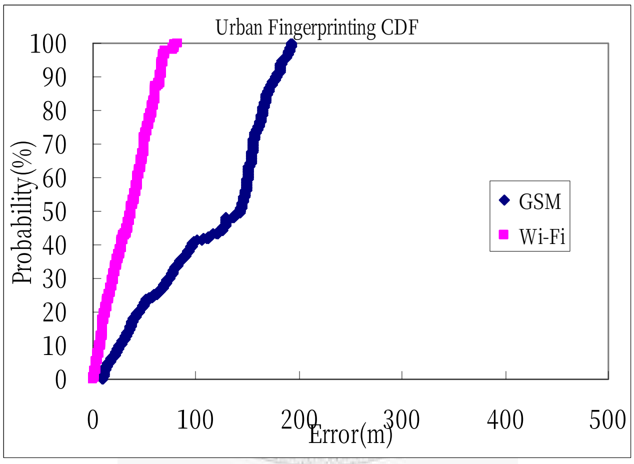

Fig. 12. CDF of GSM and Wi-Fi with Fingerprinting Algorithm in urban area

Since Centroid computes the arithmetic mean of all observed beacons, its accuracy appears to be proportional to the density of beacon distribution. Therefore, the accuracy of determining the Wi-Fi distribution was better than that of GSM distribution. Notably, the Weighted Centroid obtained worse results than basic Centroid with Wi-Fi localization, possibly because the Wi-Fi AP distribution in the area does not scatter in the same plane, but is located at various heights. Thus, Wi-Fi signal may be weak when it is actually nearby but located high above, in which case it is given a low weight, resulting in a large error distance.

Therefore, Centroid positioning would have a better performance than Weighted Centroid in an area with dense high buildings. Figures 13 (Centroid/Weighted Centroid) and 14 (Fingerprinting) summarize the localization system testing results.

Hsin-Yi District Centroid Localization

	Average(m)	Max(m)	Min(m)	STD(m)
GSM (basic)	245	448	11	129
GSM (Weighted)	161	418	18	95
Wi-Fi (basic)	64	225	2	48
Wi-Fi (Weighted)	84	218	2	48

.

Fig. 13. Centroid/ Weighted Centroid Localization results in Hsin-Yi Dist.

Hsin-Yi District Fingerprinting Localization

	Average(m)	Max(m)	Min(m)	STD(m)
GSM	113	192	9	57
Wi-Fi	35	82	1	21

Fig. 14. Fingerprinting Localization results in Hsin-Yi Dist.

The Fingerprinting localization method involves walking through the training areas, and collecting each radio scan as a single grid. According to our walking temple, the grid interval was around 2 meters. Fingerprinting localization achieved a better result than Centroid method in accuracy in this area. The average error distance of GSM localization was 113m, while that of Wi-Fi was 35m.

We believe that an error distance of 35–113m is acceptable, because that may be just the width of a boulevard. If the application does not need very high accuracy outdoors, then it is an alternative to GPS, particularly for the applications that exploit the ambiguity caused by the error [33, 34].

5.1.2 Rural Area

To assess the performance of GSM and Wi-Fi localization systems in a rural area, Long-Tan (Tao-Yuen County), a suburban area next to Taipei was chosen as the test-bed. Long-Tan is a residential region with few high buildings and commercial activities. Nine GSM cell towers and 77 Wi-Fi access points were found in the area of around 1 km^2. Figure 15 illustrates the distribution of GSM and Wi-Fi beacons in Long-Tan.

Fig. 15. GSM(Left) and Wi-Fi(Right) Distributions in Long-Tan

For Centroid localization, the average error distance was 199m with the basic Centroid algorithm, and 156m with the Weighted Centroid algorithm. In the area under Wi-Fi coverage, the average error distance was 99m with the basic Centroid algorithm, and 71m with the Weighted Centroid algorithm. Since Wi-Fi coverage is not available everywhere in Long-Tan, the Wi-Fi localization is restricted to specific regions.

Figure 16 plots the CDF (Cumulative Distribution Function) of the Centroid testing results; Fig. 17 plots the CDF of Weighted Centroid testing results, and Fig. 18 plots the CDF of Fingerprinting results in Long-Tan.

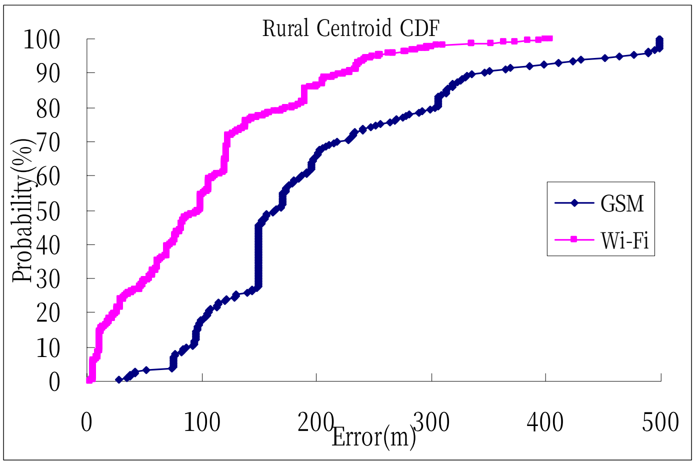

Fig. 16. CDF of GSM and Wi-Fi with Centroid Algorithm in rural area

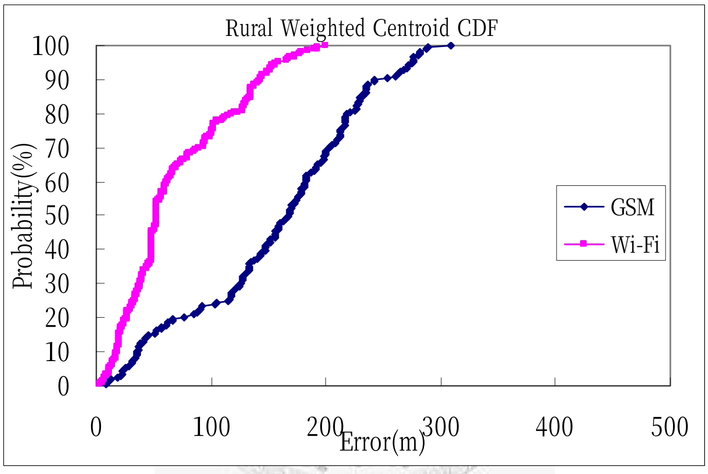

Fig. 17. CDF of GSM and Wi-Fi with Weighted Centroid Algorithm in rural area

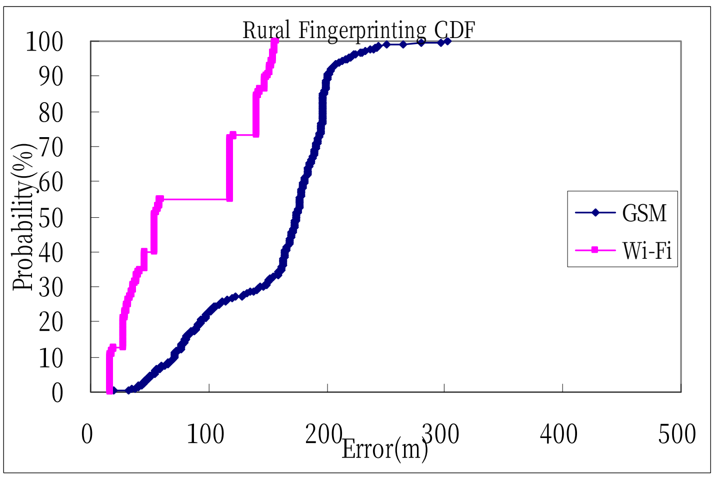

Fig. 18. CDF of GSM and Wi-Fi with Fingerprinting Algorithm in rural area

Notably, the probability distribution of Wi-Fi Fingerprinting has a few gaps owing to the discontinuity of Wi-Fi signals in the area.

Figures 19 (Centroid/Weighted Centroid) and 20 (Fingerprinting) summarize the localization system testing results in a rural area.

Centroid (Long-Tan)

	Average(m)	Max(m)	Min(m)	STD(m)
GSM(basic)	199	498	27	111
GSM(weighted)	156	308	9	75
Wi-Fi(basic)	99	403	2	81
Wi-Fi(weighted)	71	200	3	47

Fig. 19. Centroid localization results in Long-Tan.

Fingerprinting (Long-Tan)

	Average(m)	Max(m)	Min(m)	STD(m)
GSM	155	302	20	54
Wi-Fi	52	158	17	51

Fig. 20. Fingerprinting results in Long-Tan.

For Fingerprinting localization, the average error distance was 155m, and the average error distance of Wi-Fi was 52m. Since the Wi-Fi access is not available everywhere in the area, many signal gaps were observed in the tracking stage, possibly distorting the results of Wi-Fi Fingerprinting.

Significantly, the numbers of Wi-Fi access points varied according to time of day. The number of available APs was found to be greater in the night time than in the day time.

This may be because people open their APs for internet access when they come home from work in the evening, whereas they go to work in the city in the day time and switch off their APs, causing the radio emission from those APs to disappear. The unstable Wi-Fi RSSI sources may influence the tracking accuracy if training and tracking occur during different time segments. Therefore, we conclude that Wi-Fi signals may not be appropriate sources of localization systems in residential areas.

5.1.3 Campus

Since wireless networks are increasingly adopted on campuses, a university campus is likely to have a denser distribution of Wi-Fi APs than other places. Based on this assumption, NTU main campus was chosen as the testbed to evaluate the possibilities of using GSM and Wi-Fi localization systems in campus. As expected, many Wi-Fi beacons were found, while the number of GSM cell towers was slightly smaller than in a commercial area. NTU main campus has an area of $1km^2$. Twenty GSM cell towers and 859 Wi-Fi Access Points were observed around the campus. Figure 21 shows the distribution of GSM and Wi-Fi beacons in NTU.

Fig. 21. GSM(Left) and Wi-Fi(Right) distributions in NTU campus

The density of GSM cell towers on campus, measured by the Centroid localization method, was smaller than that in the Hsin-Yi District, thus yielding a slightly worse result with average error distance of 294 meters, and 193 meters when using the Weighted

Centroid algorithm. The average error distance for Wi-Fi obtained by the basic Centroid algorithm was 37m, while that obtained by the Weight Centroid algorithm was 35 meters. Although the high density of Wi-Fi AP distribution in the NTU main campus is similar to that in Hsin-Yi Dist., the result is quite different. In NTU campus, unlike Hsin-Yi Dist., the Weighted Centroid of Wi-Fi localization was slightly better than that from the Centroid algorithm, probably because most Wi-Fi APs were distributed at the same height. The heights of buildings in campus are mostly less than 6 floors, while Hsin-Yi District has many skyscrapers, including the famous Taipei 101 building with 101 floors.

Figure 22 plots the CDF of Centroid testing results; Fig. 23 plots the CDF of the Weighted Centroid test results, and Fig. 24 plots the CDF of Fingerprinting results in NTU campus.

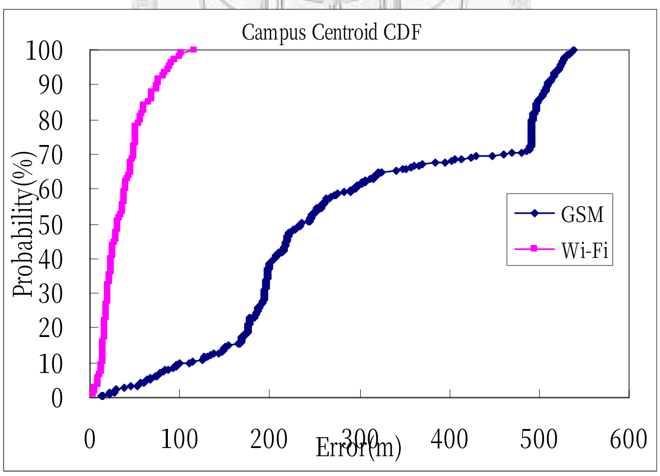

Fig. 22. CDF of GSM and Wi-Fi with Centroid Algorithm in campus

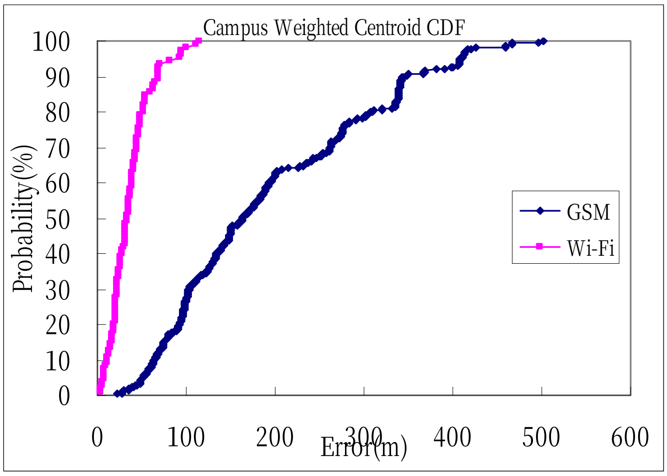

Fig. 23. CDF of GSM and Wi-Fi with Weighted Centroid Algorithm in campus

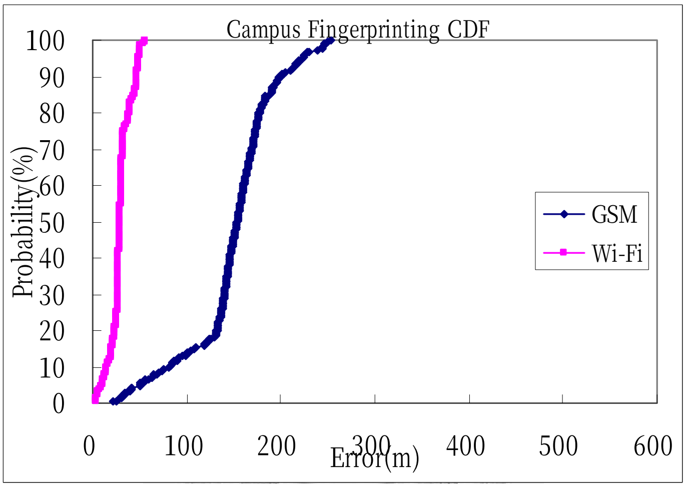

Fig. 24. CDF of GSM and Wi-Fi with Fingerprinting Algorithm in campus

Figures 25 (Centroid/Weighted Centroid) and 26 (Fingerprinting) summarize the localization system testing results in NTU campus.

NTU Centroid Localization

	Average(m)	Max(m)	Min(m)	STD(m)
GSM (basic)	294	537	12	155
GSM (Weighted)	193	502	22	114
Wi-Fi (basic)	37	115	4	25
Wi-Fi (Weighted)	35	114	3	23

Fig. 25..Centroid localization results in NTU campus

An average of 149 meters was obtained in GSM Fingerprinting localization. The GSM Fingerprinting result in NTU main campus was worse than that in Hsin-Yi Dist. The average Wi-Fi Fingerprinting localization error was 29m, which is the best outdoor result among all tested areas. We obtained better accuracy because the density of AP distribution was sufficiently high, thus yielding richer RSSI fingerprints for the Wi-Fi localization system.

Wi-Fi signals can almost certainly be found from different access points in every part of campus. Therefore, the good result of Wi-Fi localization makes Wi-Fi a good candidate for localization system on campus. An average error of 29–37 meters should be good enough for a student to distinguish between different buildings. Alternatively, the localization system can be combined with the campus tour guide system.

NTU Fingerprinting Localization

	Average(m)	Max(m)	Min(m)	STD(m)
GSM	149	253	22	45
Wi-Fi	29	60	3	20

Fig. 26. Fingerprinting Localization results in NTU campus

5.1.5 Indoors

To study the feasibility of localization systems in omni-environments, experiments were also conducted indoors. The 3rd floor of the NTU CSIE department building was utilized as the testbed. Because GPS signals are not available indoors, beacon locations could not be collected for running Centroid localization as was done outdoors. Figure 27 displays the training grids in the CSIE building.

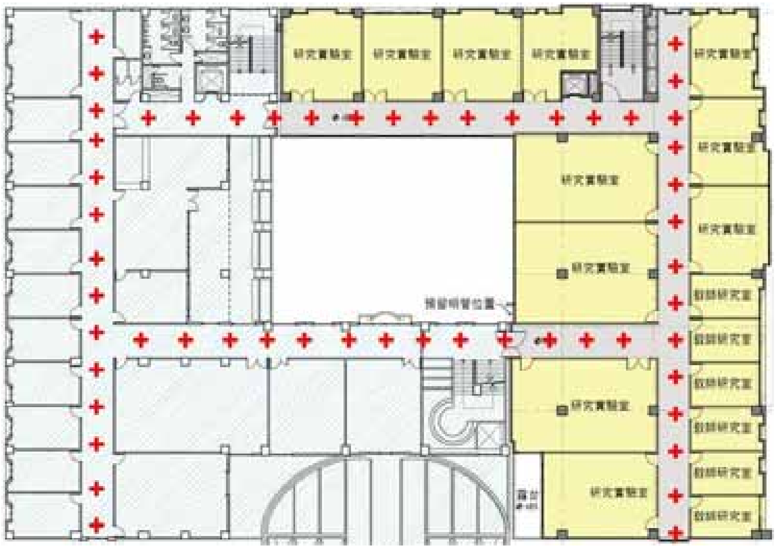

Fig. 27. The 3rd floor of CSIE building and grids for Fingerprinting

For indoor Fingerprinting localization, the grid size was set to 2m×2m, and 20 RSSI fingerprints were collected in a static point in the training stage. The grids were distributed along the hallway. The error was found to be quite large if the cell ID was applied for GSM localization, which can provide 5–6 cell IDs at a time. The system can even estimate the location in the opposite corner (around 40m away). Therefore, to improve the accuracy, channel ID rather than Cell ID was used as the beacon ID in GSM indoor localization, because the channel ID can provide richer signals, typically detecting 15–20 channels at a time. Wi-Fi localization found 18–20 simultaneous AP signals in the CSIE building.

Figure 28 plots the CDF of Fingerprinting results in CSIE building.

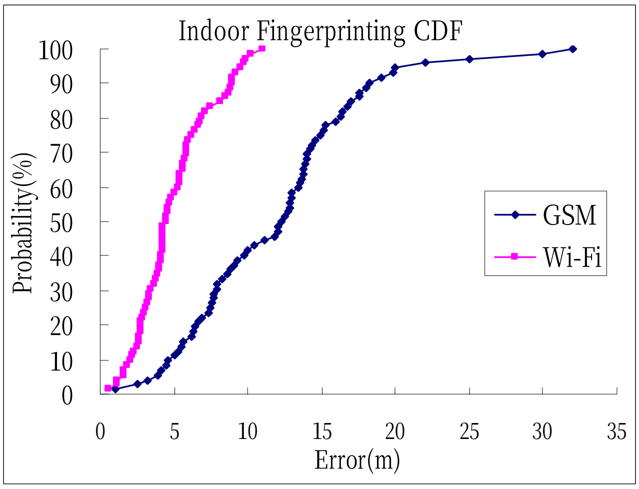

Fig. 28. CDF of GSM and Wi-Fi Indoor Fingerprinting in CSIE building

The experimental results indicate an average error of 4.9 meters with Wi-Fi localization, and an average error of 10.9 meters with GSM localization. These results demonstrate that Wi-Fi localization can provide a better precision and accuracy in indoor space, provided that sufficient Wi-Fi radio sources are provided.

If cell ID was adopted rather than GSM channel ID as the beacon identity, then the accuracy was normally over 20m. The error distance itself was not measured, because the result is no better than that of random guessing. Figure 29 shows the summary of Fingerprinting localization testing results indoors.

Indoor Fingerprinting in CSIE Building

	Average(m)	Max(m)	Min(m)	STD(m)
GSM	10.9	32	1	6
Wi-Fi	4.9	11	0.6	2.4

Fig. 29. Indoor Fingerprinting results in CSIE building

5.1.6 Beacon numbers vs. Accuracy

In addition to above experiments, we perform an experiment to observe the relationship between the accuracy and the observed beacon numbers with Fingerprinting algorithm.

The channel ID method of GSM localization is utilized in the experiment because the numbers(up to 20) of observed channels are good enough for the comparison. The result is displayed in Figure 30. From the figure, we found the accuracy is proportional to the simultaneous observed beacon number. The higher accuracy we can have form the localization system as the number of observed beacons increases. We also found from the figure that with the same number of beacons, the accuracy of GSM is typically worse then Wi-Fi localization system.

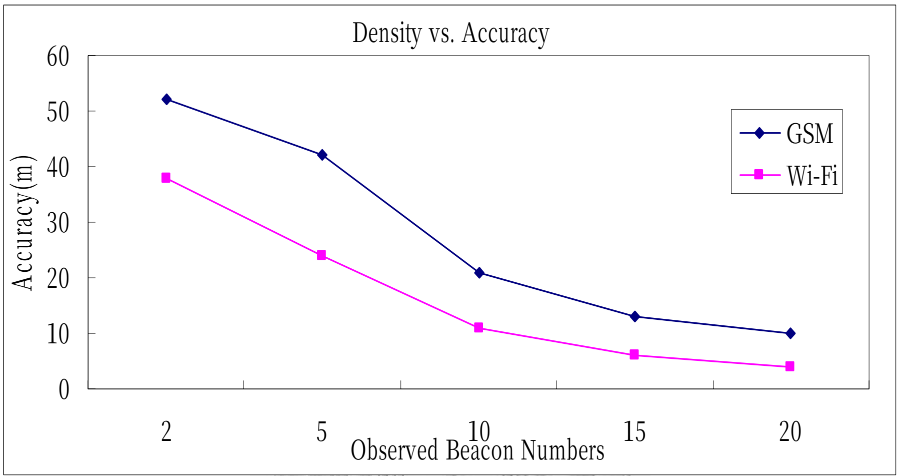

Fig.30. Beacon numbers vs. Accuracy

5.1.7 Discussion

Experimental results reveal that the accuracy of Wi-Fi was generally 2–8 times higher than that of GSM localization. The Weighted Centroid algorithm was found to improve accuracy of GSM localization by 30%~50%, compared with the basic Centroid algorithm, the two algorithms yielded similar results with the Wi-Fi localization system. We conclude that the shorter transmission range of Wi-Fi means that its distribution tends to be denser than that of GSM. The weighted method would not improve significantly in such a dense-beacon environment, because the mobile device observes similar signal strengths, and giving them similar weights. Additionally, the accuracy of Wi-Fi localization system was proportional to the density of Wi-Fi access points in our experiments, but density did not significantly affect the results of the GSM localization system.

Wi-Fi localization system can provide better accuracy than GSM, as mentioned above, but Wi-Fi signal gaps were often observed in suburban and even urban area. Therefore, if Wi-Fi localization is used on its own, then an object may often lose its position in an area with sparse Wi-Fi access point density. Conversely, GSM provides broader coverage than Wi-Fi, although it has a lower accuracy than the Wi-Fi localization system. The GSM localization system can at least guarantee to find the position of an object within a reasonable error range.

Our outdoor experimental result(113m) of the GSM localization is slightly worse than the result(94m) presented in [27]. We believe the differences might be derived from the implementations of Fingerprinting algorithm. We utilize all observed GSM cells to calculate the Euclidean distance and give the mismatched GSM cells penalties, while [27] chooses the n strongest GSM cell signals to calculate the Euclidean distance. Indoor experimental result(5m) of the GSM localization in this work is also slightly worse than the result(2.5m) presented in [13]. In [13], they observed up to 29 GSM channels indoors, but we normally observed 15~18 GSM channels in CSIE building. That is one possible reason to explain the differences between these two works, since more signal sources can provide richer radio fingerprints.

5.2 Other evaluation metrics

As well as the precision and accuracy compared above, some other metrics can be employed OR utilized to evaluate the performance of the GSM/Wi-Fi localization systems.

Infrastructure Availability:

Mobile station based methods of implementing localization system involves effort in training and calibration. First, in the training stage, the locations of the beacons or the radio fingerprints on the grids need to be discovered. The radio map database is used later for tracking. Because the infrastructure may change over time, the radio map needs to be calibrated to maintain the accuracy.

GSM is a fairly stable network, since the costs of adding and removing a cellular tower is high. Operators tend not to change the infrastructure frequently. Wi-Fi is a relatively unstable infrastructure because some of the radio sources are from residential access points. The Wi-Fi localization system might adopt all available Wi-Fi signals, irrespective of whether they are from public or private access points. This work has found that Wi-Fi signals from public access points are generally stable. Wi-Fi radio sources from residential access points are unstable because they are usually switched off if not used. This is a constraint and potential hazard when utilizing a Wi-Fi localization system.

Hardware Capability:

Cellular phones currently support a variety of communication peripherals, such as Wi-Fi, Bluetooth and infrared. GSM is the most basic function of a regular cellular phone, even with 3G cellular phones, which are normally designed with support for GSM. GSM is currently the most widely available radio source that can be adopted with a mobile phone. Some high-end cellular phones are equipped with Wi-Fi or even GPS modules. These cellular phones have the flexibility of adopting various localization systems, including the GSM and Wi-Fi localization systems mentioned herein.

Power and computing consumption:

Computing power is proportional to the electrical power consumption. Heavy processor loading on a mobile device reduces the battery life. Experiments results show that Wi-Fi localization consumes more power than GSM. With Dopod 586W, the system is run with only GSM localization, and then the phone can continuously run for 24 hours. If Wi-Fi is activated, then the phone can run for only 5 hours. Since Wi-Fi localization system needs to estimate an object's location in real-time, it prevents the phone from entering sleep mode. Because cellular phones are designed primarily for voice communication, their designers may pay most attention to power saving in the GSM mode. Although Wi-Fi may have its own power saving features, the localization does not work if the handset enters sleep mode. Hence, the constraints of power consumption on cellular phones mean that Wi-Fi localization is not appropriate for a cellular phone.

Figure 29 summarizes the above discussions and the experimental results.

	Accuracy and Precision	Infrastructure Availability	Hardware Capability	Power Consumption
GSM		★	★	★
Wi-Fi	★			

Fig. 31. Performance summary table (★ stands for a better performance)

5.3 Practical Issues

Some practical issues that would affect the results of a localization system were discovered during the experiments. These factors have to be addressed if the localization system is going to be deployed in the real world.

5.3.1 Limited RSSI sources

If the application, like library guidance system, needs accurate location information, then the selection of a rich source of beacons is a critical factor to bringing sound localization results. However, the embedded design of most cellular phones means that most users probably do not know how to read RSSI sources from radio modems or device drivers. Even if the data could be read from some of these cellular phones, it might be less than the expected numbers to constitute an accurate localization system. Experiments results demonstrate that Dopod 585 or 586w can output 6–7 cell IDs with RSSI, which may not be sufficient to achieve a good accuracy. The average error was around 150 meters in our experiments, whereas Wi-Fi can achieve 29 meters with around 15–20 AP readings.

For GSM localization, if BCCH (Broad Control Channel), the channel ID, is utilized instead of Cell ID, then richer signal sources can be observed, typically 15–18 readings from different channels in our tested environments. An accuracy of 11 meters can then be achieved indoors if channel ID is applied to reconstruct the GSM localization system. However, owing to the nature of channel reuse in GSM networks, moving across several cells causes the channel ID to be duplicated. Therefore, the channel ID is only suitable for use in a small area, where each channel number is unique.

Experiment results reveal that a Wi-Fi localization system seems to be good in both campus and commercial area. Accuracies of 29m outdoors and 5m indoors can be achieved. Conversely, rural areas have fewer Wi-Fi signal sources than GSM cell, or nearly none. Therefore, Wi-Fi RSSI cannot be applied to locate objects in a rural environment.

5.3.2 Resource constraints on mobile devices

Filters such as KNN (K-nearest neighbors), Cluster or Particle filters usually have to be applied when adopting a Fingerprinting localization system or other filters to find the grid with highest probability once all possible grids have been found. These methods would be valuable, but they introduce additional computing efforts, since the mathematical calculation for the filters consume significant computing power on the device. Due to the limited computing resources on cellular phones or mobile devices, complex filters or motion models should not be applied to the tracking programs.

By contrast, the Centroid algorithm only employs straightforward arithmetic addition and division during the tracking stage. It consumes few CPU resources, and therefore may be a good solution for a localization system on a mobile device, which typically has limited computing resources.

From the data storage point of view, in the Fingerprinting localization system, the data occupies about 850 bytes (including 33 beacons) in each grid, assuming a grid size of 10×10 meters. According to the log sample above, a database for an area of 1km^2 requires at least 10,000×850 = 8,500,000 bytes. Taipei has an area of 272km^2, and therefore needs 8,500,000×272 = 2,312,000,000 bytes for its localization database. This is too big volume even put for a 2G memory card on a mobile device. The typical storage space of a beacon in a Centroid localization system is 43 bytes. Given that average beacon density in an urban area is 500beacons/km^2 on average, 43×500×272 = 58,480,000 bytes are necessary to complete a city wide radio map of Taipei. The Centroid algorithm is a fairly feasible way of designing a large-scale localization system on mobile devices.

5.3.3 Training condition

In Centroid localization, a number of beacons need to be found in the training stage, since the tracking result is shown to be proportional to the number of reading beacons. The Centroid method was employed during the experiments to locate all available beacons. The training quality depends on the number of sampling points and the stability of observed signal strength. Experimental results show that fewer beacons are obtained when collecting the radio sources by car driving than by walking. This is because some of the weak signals may be ignored during driving, and the fluctuation of the signal strength may confuse the training program. Experimental results indicate that signals can be collected effectively by riding a bicycle or walking.

The accuracy of Fingerprinting localization may depend on the stability of signal sources. Because the radio signal fluctuates frequently with different weather and environments, stable training data are necessary to avoid significant errors during the tracking stage. Experimental results show that the quality of Fingerprinting localization depends heavily on the quality of training. Increasing the time spent on each grid during data collection enhances the tracking accuracy well.

5.3.4 Scale of RSSI readings

The scale of radio signal reading was found to significantly affect the accuracy of location estimation. The scale of Wi-Fi RSSI readings using Dopod 586W was 10dbm. The readings from the Wi-Fi driver were mostly −90dbm, −80dbm or −70dbm from our observation. Because the device has only 3 RSSI types, the localization system can easily discover grids with similar radio fingerprints during the tracking stage, and obtain worse results in consequence.

After the device was changed to Dopod 900, which can provide 1dbm scale in Wi-Fi RSSI readings, the tracking results improved significantly from 100 meters to 20–30 meters. Hence, we believe the accuracy of a localization system is proportional the level of detail of information that a device can provide.

Chapter 6

Hybrid System

Following the experimental results, this chapter discusses the feasibility of building a hybrid localization system that combines the benefits of both GSM and Wi-Fi localization systems.

6.1 Motivation

Experimental results reveal that GSM and Wi-Fi each have their own advantages in specific areas or domains. For instance, urban areas have many GSM cellular towers and Wi-Fi access points, so are good for both GSM and Wi-Fi localization systems. Rural areas have fewer GSM cellular towers than urban areas have, and have many gaps in the Wi-Fi signal gaps. This work recommends applying GSM localization system in such an environment, because GSM signals provide better coverage than Wi-Fi signals. Wi-Fi localization produces good results on campus, where Wi-Fi signals are pervasive. Wi-Fi can provide accurate localization in an indoor environment if the signal is available and the number of observed Wi-Fi fingerprints is large enough. Figure 30 shows an environment with varied density of GSM and Wi-Fi.

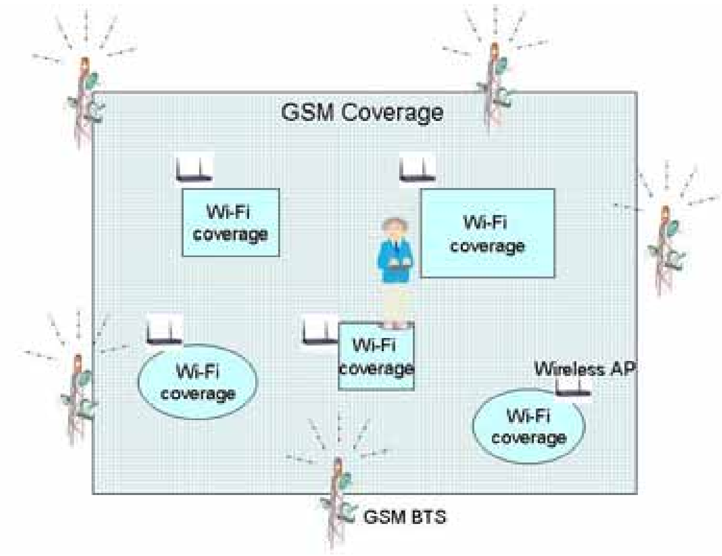

Fig. 32. A hybrid environment with different GSM or Wi-Fi density

GSM and Wi-Fi are normally treated as two different localization systems. Individual radio maps need to be trained and individual program need to be loaded, before starting to run the system. The system must be switched manually once the application requires high accuracy in complex environments,. Hence, a hybrid system that can automatically switch between GSM and Wi-Fi localization is needed.

6.2 Hybrid Architecture

The accuracy of a localization system is proportional to the density of valid beacons according to our experimental results. Therefore, the beacon density was taken as the criterion for switchover between different systems

Wi-Fi localization generally has higher accuracy than GSM. However, GSM coverage is broader than Wi-Fi in terms of infrastructure availability. Therefore, a GSM localization system can be expected to work normally in most places. A better precision and accuracy can be expected from a Wi-Fi localization system in areas with good Wi-Fi coverage.

The system begins by loading a radio map database, which consists of GSM and Wi-Fi beacon locations or RSSI fingerprints. It then detects the density of GSM and Wi-Fi beacons nearby. If the density of GSM signals is higher than that of Wi-Fi, then the hybrid system runs GSM localization automatically. The hybrid system meanwhile continues observing the density of Wi-Fi signals, to determine whether it is now above that of GSM signals, in which case it changes the program to the Wi-Fi localization system. Figure 31 depicts the system flow.

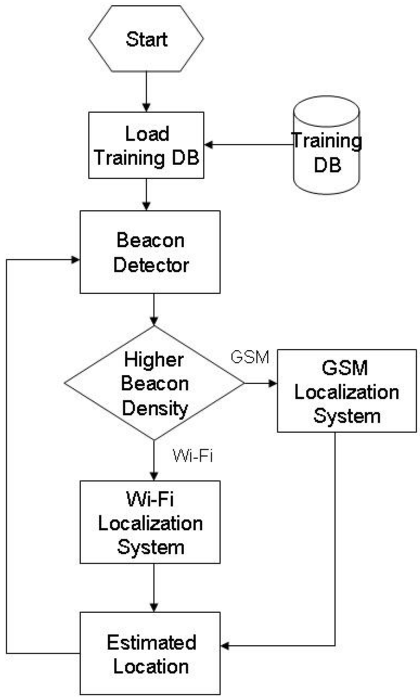

Fig. 33. System flow of GSM/Wi-Fi Hybrid Localization

GSM can provide wider coverage, and Wi-Fi can provide higher accuracy in general. The hybrid system is more accurate than just a single localization system, because it combines the advantages of both, and can solve the Wi-Fi signal gap problem.

6.3 Challenges

Because the localization in the hybrid system is adaptive to the density of beacons, both the GSM and Wi-Fi radio map databases need to be stored on the mobile device. This creates the problem of limited storage on mobile devices, as discussed in Chapter 5.3.2. A possible solution is to setup a backend server, which stores all available radio map databases, somewhere on the network. The mobile devices can request the server to provide corresponding radio maps on demand, and thus decrease the required storage space and computing effort, while the hybrid localization systems are activated.

Chapter 7
Conclusion

This work examines the feasibility of incorporating GSM and Wi-Fi localization systems in indoor and outdoor environments, particularly in a large outdoor area. Several combinations of experiments are performed to show the expected precision and accuracy of localization systems using) different algorithms. Experimental results indicate that with small training efforts, an accuracy of 29 meters can be obtained outdoors where this value is less than the width of an ordinary street. The error distance indoors in our experiments is less than 5m. We believe that Fingerprinting is appropriate for both indoor and outdoor environment, since it can provide higher accuracy, but its training and calibration costs are considerably higher than those of other algorithms. This is a cost issue while planning to deploy such a system. The error distance of the Centroid algorithm can achieve 37 meters outdoors in average in this work. Because the training process of the Centroid algorithm takes less time and involves little calibration effort, the Centroid algorithm is an appropriate candidate for outdoor localization on mobile devices.

The experiments in this work do not apply motion models, instead simply performing comparisons with raw data. A good motion model is strongly needed to improve accuracy by filtering out noises. However, if a motion model is introduced, then the cellular phone has to consume additional computing resources for extra mathematical operations. Resource consumption is a crucial issue with current mobile devices or cellular phones. Nonetheless, as hinted in “Moore’s Law”, this issue is likely to be resolved on mobile devices soon.

For future works, the study of automatic training and calibration should be a vital factor in mobile station based localization systems, particularly in dynamic environments. Additionally, because GSM and Wi-Fi are available indoors and outdoors, but provide different levels of strength in localization, the construction of a GSM/Wi-Fi hybrid localization system, which is practical in real environments, is of interest.

Bibliography

[1] G. Chen, D. Kotz, “A Survey of Context-Aware Mobile Computing Research", Technical Report TR2000-381, Department of Computer Science, Dartmouth College, November 2000.

[2] Michael Beigl, Albert Krohn, Tobias Zimmer and Christian Decker, “Typical Sensors needed in Ubiquitous and Pervasive Computing”, First International Workshop on Networked Sensing Systems (INSS) 2004, Tokyo, Japan, June 22-23. 2004.

[3] J. Hightower, G. Borriello, “Location Systems for Ubiquitous Computing”, IEEE Computer, August 2001.

[4] A. Ward, A. Jones, A. Hopper, “A New Location Technique for the Active Office”, IEEE Personal Communications, Vol. 4, No. 5, October 1997, pp 42-47.

[5] N. B. Priyantha, A. Chakraborty, H. Balakrishnan, “The Cricket Location-Support System”, In Proceedings of the Sixth Annual International Conference on Mobile Computing and Networking (MOBICOM 2000), Boston, MA, USA, August 2000.

[6] P. Bahl and V. N. Padmanabhan, “RADAR: An In-Building RF-Based User Location and Tracking System”, Proceedings of IEEE Infocom 2000, Tel-Aviv, Israel, March, 2000, pages 775-784.

[7] A. LaMarca, et al, "Place Lab: Device Positioning Using Radio Beacons in the Wild," in Proceedings of the Third International Conference on Pervasive Computing, May 2005.

[8] Want, R., Hopper, A., Falcão, V., Gibbons, J. The Active Badge Location System. ACM Transactions on Information Systems, January 1992.

[9] Brumitt, B., Meyers, B., Krumm, J., Kern, A., and Shafer, S. “EasyLiving: Technologies for Intelligent Environments”, In Proceedings of Handheld and Ubiquitous Computing, September, 2000.

[10]Krumm, J., Harris, S., Meyers, B., Brumitt, B., Hale, M., and Shafer, S., “Multi-Camera Multi-Person Tracking for Easy-Living”, in Proceedings of IEEE Workshop on Visual Surveillance, July, 2000.

[11]N. Priyantha, A. Charkraborty, and H.Balakrishnan, “The cricket location support system,” Proc. 6th Annual ACM Int’l Conf. Mobile Computing and Networking, August, 2000.

[12]Robert J. Orr and Gregory D. Abowd, “The Smart Floor: A Mechanism for Natural User Identification and Tracking”, In Proceedings of the Conference on Human Factors in Computing Systems (CHI 2000), The Hague, Netherlands, April, 2000.

[13]Veljo Otsason, Alex Varshhavsky, Anthony LaMarca, Eyal de Lara, “Accurate GSM Indoor Localization”, In Proceedings of the Seventh International Conference on Ubiquitous Computing (ACM Ubicomp 2005), Tokyo, Japan, September, 2005, pages 141-158.

[14]Chuang-wen You, Yi-Chao Chen, Ji-Rung Chiang, Polly Huang, Hao-hua Chu, Seng-Yong Lau, Sensor-Enhanced Mobility Prediction for Energy-Efficient Localization, in Proceedings of Third Annual IEEE Communications Society Conference on Sensor, Mesh and Ad Hoc Communications and Networks (IEEE SECON 2006), September, 2006.

[15]L.-W. Chan, J.-R. Chiang, Y.-C. Chen, C.-N. Ke, J. Hsu, H.-H. Chu, “Collaborative Localization: Enhancing WiFi-Based Position Estimation with Neighborhood

Links in Clusterse, In Proceedings of International Conference on Pervasive Computing (Pervasive 06), May, 2006.

[16]http://pols.sourceforge.net/

[17]UbiSense, http://www.ubisense.net

[18]Scooter Willis and Sumi Helal, A Passive RFID Information Grid for Location and Proximity Sensing for the Blind User, University of Florida Technical Report number TR04-009.

[19]http://www.dopodasia.com/dopod/taiwan

[20]http://www.mactiontech.com/

[21]AsiaMedia http://www.asiamedia.ucla.edu/article.asp?parentid=48362

[22]Ekahau. http://www.ekahau.com.

[23]Dieter Fox, Jeffrey Hightower, Lin Liao, Dirk Schulz, Gaetano Borriello, "Bayesian filtering for location estimation", IEEE Pervasive Computing, 2(3):24-33, July-September 2003.

[24]Jeffrey Hightower, Gaetano Borriello, “Particle filters for location estimation in ubiquitous computing: A case study”, In Proceedings of the Sixth International Conference on Ubiquitous Computing (Ubicomp 2004), pages 88-106, September, 2004.

[25]Dirk Schulz, Dieter Fox, Jeffrey Hightower, “People tracking with anonymous and id-sensors using rao-blackwellised particle filters”, In Proceedings of the Eighteenth International Joint Conference on Artificial Intelligence (IJCAI '03), pages 921-926. Morgan Kaufman, 2003.

[26]Vinay Seshadri, Gergely V. Zaruba, Manfred Huber, “A bayesian sampling approach to in-door localization of wireless devices using received signal strength

indication ” , In Proceedings of the Third IEEE International Conference on Pervasive Computing and Communications (PERCOM 2005), March, 2005.

[27]M. Chen, T. Sohn, D. Chmelev, D. Haehnel, J. Hightower, J. Hughes, A. LaMarca, F. Potter, I. Smith, A. Varshavsky, "Practical Metropolitan-Scale Positioning for GSM Phones," In Proceedings of Eighth International Conference on Ubiquitous Computing (ACM Ubicomp 2006), September, 2006.

[28]T. Sohn, A. Varshavsky, A. LaMarca, M. Chen, T. Choudhury, I. Smith, S. Consolvo, J. Hightower, W. Griswold, E. de Lara, “ Mobility Detection Using Everyday GSM Traces ” , In Proceedings of Eighth International Conference on Ubiquitous Computing (ACM Ubicomp 2006), September, 2006.

[29]D. Hahnel, W. Burgard, D. Fox, K. Fishkin, M. Philipose, “ Mapping and Localization with RFID Technology “ , In Proceedings of IEEE International Conference on Robotics and Automation (IEEE ICRA 2004), April, 2004.

[30]Lionel M. Ni, Yunhao Liu, Yiu Cho Lau, Abhishek P. Patil, “ Landmarc: Indoor Location Sensing using Active RFID ” , In Proceedings of the First IEEE International Conference on Pervasive Computing and Communications (PERCOM 2003), March 2003.

[31]Shun-yuan Yeh, Chon-in Wu, Keng-hao Chang, Hao-hua Chu, Jane Yung-jen Hsu, The GETA Sandals: A Footprint Location Tracking System, accepted by ACM/Springer Journal of Personal and Ubiquitous Computing (PUC), special issue for Location- and Context-Awareness, 2006.

[32]Masateru Minami, Yasuhiro Fukuju, Kazuki Hirasawa, Shigeaki Yokoyama, Moriyuki Mizumachi, Hiroyuki Morikawa, Tomonori Aoyama, "Dolphin: A practical approach for implementing a fully distributed indoor ultrasonic positioning system",

In Proceedings of The Sixth International Conference on Ubiquitous Computing (ACM UbiComp 2004), pages 347-365. September, 2004.

[33]Gregor Broll, Steve Benford, Leif Oppermann, “Exploiting Seams in Mobile Phone Games”, PerGames 2006

[34]Adam Drozd, Steve Benford, Nick Tandavanitj, Michael Wright, and Alan Chamberlain, “Hitchers: Designing for Cellular Positioning”, ACM Ubicomp 2006

[35]Yu-Chung Cheng, Yatin Chawathe, Anthony LaMarca and John Krumm, “Accuracy Characterization for Metropolitan-scale Wi-Fi Localization”, In Proceedings of The Third International Conference on Mobile System, Applications, and Services(Mobisys 2005).

[36]https://www.jiwire.com/press-taipei-network.htm