

## Exploiting the Associated Information to Locate Mobile Users in Ubiquitous Computing Environment

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**Abstract**— Although GPS is deemed as ubiquitous outdoor localization technology, we are still far from a similar technology for indoor environments. Though a number of techniques are proposed for indoor localization, they are separated efforts that are way from a real ubiquitous localization system. Our real-world experience from InSpace, a pervasive computing system with wireless devices to provide intelligent services to users, shows that locating mobile users remains very challenging due to various interfering factors. We analyze real traces of mobile phones carried by users and find that mobile users exhibit temporal-spatial stability and neighborhood relativity. Motivated by this observation, we develop a Mobile Boundary Localization approach, MBL, to exploit the associated information to locate mobile users. This localization approach uses different treatment in different conditions and lets each mobile phone try to estimate its possible location range. We have implemented and evaluated MBL by extensive real-world experiments in InSpace and simulations. The results demonstrate that MBL significantly outperforms state-of-the-art localization approaches with more accurate, efficient, and consistent performance.

**Keywords**-Localization; Ubiquitous Computing; Mobile

### I. INTRODUCTION

The ability to automatically determine locations is critical to various applications in ubiquitous computing environment [1, 2, 26, 27, 28]. Meanwhile, many applications are in mobile wireless network environments. For example, wireless devices are attached to tourists in a scenic spot, staffs in the office, patients in a hospital, soldiers in a battlefield, cargos in logistics, and animals in the wild. It is therefore important to support efficient localization for wireless devices in mobile network environments.

The Global Positioning System (GPS) is a ubiquitous localization approach, but usually fails to function in indoor environments due to poor reception of satellite signals [3]. Such a fact motivates researchers to develop new localization algorithms.

A widely-adopted solution is to deploy a wireless network with some location-aware nodes (called seeds) which know their locations and provide location information

to other ordinary nodes to assist them in estimating their locations. Existing localization approaches mainly fall into two categories: range-based approaches (e.g. TOA [4], TDOA [5], AOA [6]) and range-free approaches (e.g. APIT [7], DV-hop [8]).

Most of the existing localization approaches are designed for static wireless networks. The intuitive solution for a mobile network is to divide time into discrete time intervals. During each time interval, a mobile network can be treated as a static network and then located by an existing localization approach for static networks. However, such approaches are hard to reach the ideal localization effect.

There are only a limited number of recent works that explicitly take into account the issue of dynamic localization in mobile networks [9, 10, 11]. Most of these approaches do not fully exploit the available information. They overly depend on the location information of seeds, and overlook the associated information among ordinary nodes. Moreover, they carry out simulation to evaluate performance of their approaches based on synthetic mobility traces. The applicability of those approaches remains unknown in real systems, especially in large scale networks.

In order to make better use of available information, the radio localization systems are proposed. Most popular systems are based on the measurement of Received Signal Strength (RSS) [12, 13] from reference nodes, which can thus compute their distances to the targets according a certain radio propagation model. Unfortunately, this approach is inaccurate in indoor scenarios, because accurate channel modeling is impractical, due to high spatial variability. Therefore, fingerprinting techniques [14, 15] are proposed recently. However, it needs a pre-training effort to generate a radio map of fingerprints.

In this paper, we propose MBL, a Mobile Boundary Localization approach for mobile users in the indoor environment without requiring any pre-training phase. This work is motivated by the need of accurate location information in InSpace, a pervasive computing system with various wireless devices to provide intelligent services to users. An indispensable element in InSpace applications is

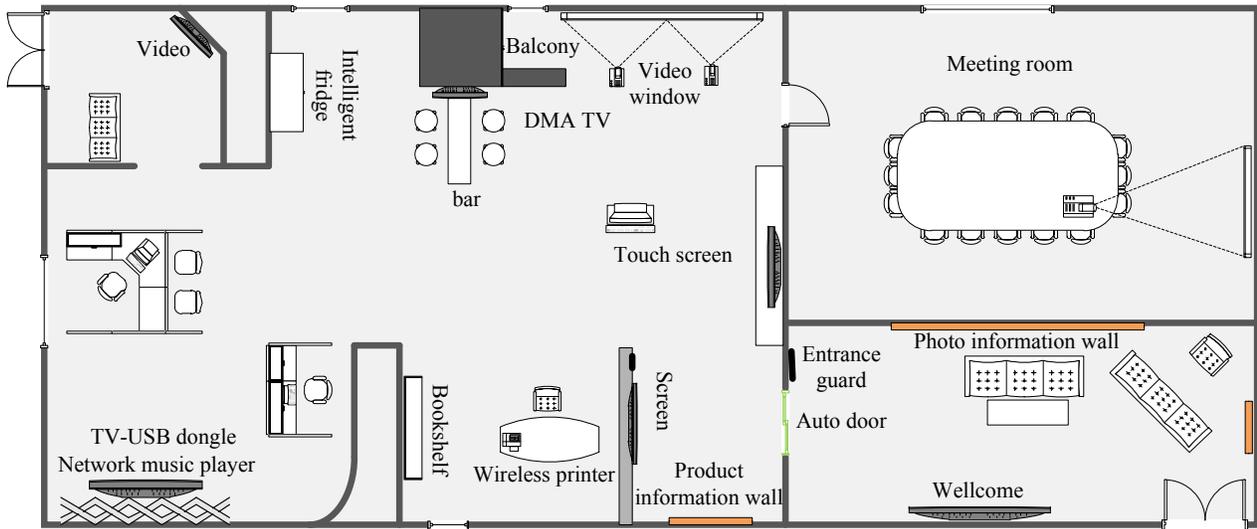


Figure 1: InSpace deployment in an indoor environment

the location of mobile users, which is the foundation of context-awareness to help system push appropriate services voluntarily. For example, when a user intends to enter a dark room, the light will be turned on automatically in advance. To achieve this goal, system needs first to obtain the user's current position and the trend of movement.

Considering that mobile phone becomes increasingly popular, we design our localization approach based on mobile phone carried by people inside a building. The central idea of MBL is as follows. The mobile phones capture users' movement traces using built-in sensors (*e.g.* accelerometer and gyroscope). At the same time, every mobile phone exchanges location information with its neighbors to assist each other in improving the localization accuracy.

MBL faces the following challenges in a practical system. (i) Not all the mobile phones have built-in sensors. (ii) Accelerometers and gyroscope have noisy measurement with inevitable errors. (iii) Accurate location information of users is needed for most ubiquitous computing applications. MBL is designed for mobile ubiquitous environment to address the above challenges. The contributions of our work are summarized as follows.

- **We constantly exploit the associated information to locate mobile users.** The novelty lies in the idea that both seeds and ordinary nodes provide useful hints for localization. Our approach utilizes the temporal-spatial stability and neighborhood relativity of mobile users to improve location accuracy.
- **We estimate mobile user's possible location range instead of a concrete location.** We believe that in ubiquitous computing applications, an appropriate location range of mobile user is more appropriate and

reasonable than a concrete location with uncertain errors. Additionally, we propose a novel metric to evaluate the performance for location range estimation.

- **We propose an efficient and universal motion track estimation method.** This method uses different treatments in different conditions and lets each node try to update its location range independently.
- **We build InSpace system with various mobile wireless devices inside a building and evaluate MBL.** Our extensive experiments and simulation results demonstrate that MBL outperforms existing approaches in terms of accuracy, efficiency, and performance consistency.

The rest of this paper is organized as follows Section II presents motivation of our work. The design of MBL is elaborated in Section III, followed by performance evaluation in Section IV. Section V briefly reviews the related work. We conclude in Section VI.

## II. MOTIVATION

InSpace is an ongoing research project that aims at building a multi-purpose smart space system in ubiquitous computing scenarios. We focus on techniques and systems to use wireless devices to perceive the activities and context of people and groups, and then exploit those models to provide better services.

A prototype system of InSpace is shown in Figure 1. The various devices are deployed inside the building of a 10m\*24m region. InSpace contains two kinds of devices: intelligent devices and non-intelligent devices. An intelligent device is any type of equipment, instrument, or machine

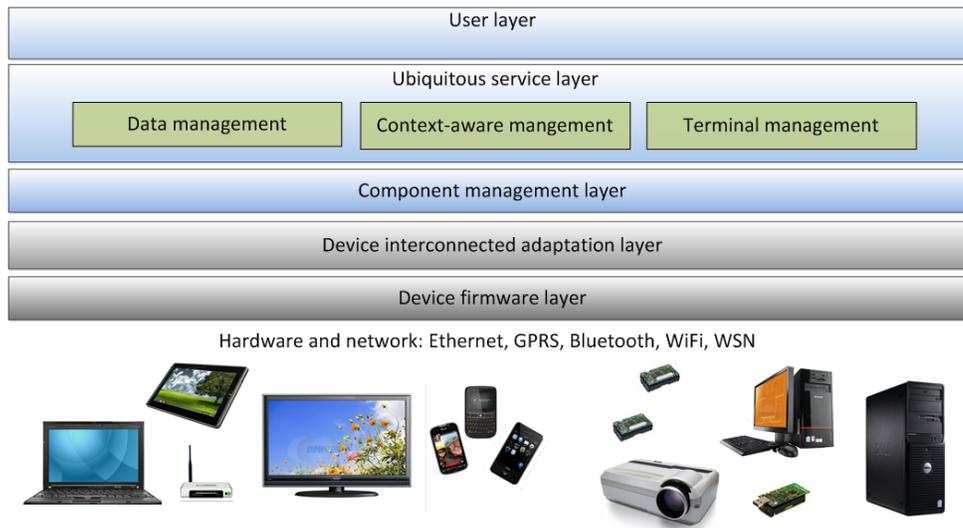


Figure 2: InSpace system architecture

Table 1: The type of mobile phones

Type	Built-in sensors
I	Communication module
II	I, GPS
III	II, accelerometer, gyroscope, <i>etc.</i>

having the computing capability such as server, laptop, PDA and smart phone. Comparatively, a non-intelligent device is the equipment without computing capability working under the control of other intelligent devices such as curtain, light, air-condition, projector, printer, *etc.*

Figure 2 shows the system architecture of InSpace. In order to use these devices to provide intelligent service, we need to obtain user's precise position first. Typically, location information is the foundation of context-aware in the ubiquitous management layer. MBL is designed for this purpose.

Our approach relies on three basic assumptions: (i) that all the mobile phones can communicate with their neighbors directly within a certain range based on Bluetooth, (ii) that some mobile phones are equipped with GPS, accelerometer and gyroscope, and (iii) that there are some WiFi APs cover the service area. For ease of presentation, we divide the mobile phones into three types as shown in table 1.

We use the Bluetooth low energy (BLE) technology to achieve peer-to-peer communication of mobile phones. BLE is the newest 4.0 wireless radio technology, aimed at principally low-power and low-latency. It can be applied for various wireless devices within a short range. This facilitates a wide range of applications in ubiquitous computing

Table 2: Classic Bluetooth vs. BLE

Technical Specification	Classic Bluetooth	Bluetooth low energy
Distance/Range	30 feet (class 2)	>300 feet
Application throughput	0.7-2.1 Mb/s	0.21 Mb/s
Active slaves	7	Implementation dependent
Security	64/128-bit	128-bit CCM
Latency	<6 s	<6 ms
Power consumption	varies with class	0.01 to 0.5
Peak current consumption	<30 mA	<20 mA
Service discovery	Yes	Yes

environment. We do experiment to compare BLE with classic Bluetooth and list the technical details in Table 2.

BLE technology uses a 32 bit access address on every packet for each slave, allowing billions of devices to be connected. The technology is optimized for one-to-one connections while allowing one-to-many connections using a star topology. Due to the quick connections and disconnections, data can be transferred in a mesh topology without the complexities of maintaining network. These features of BLE are in full compliance with requirements of our applications.

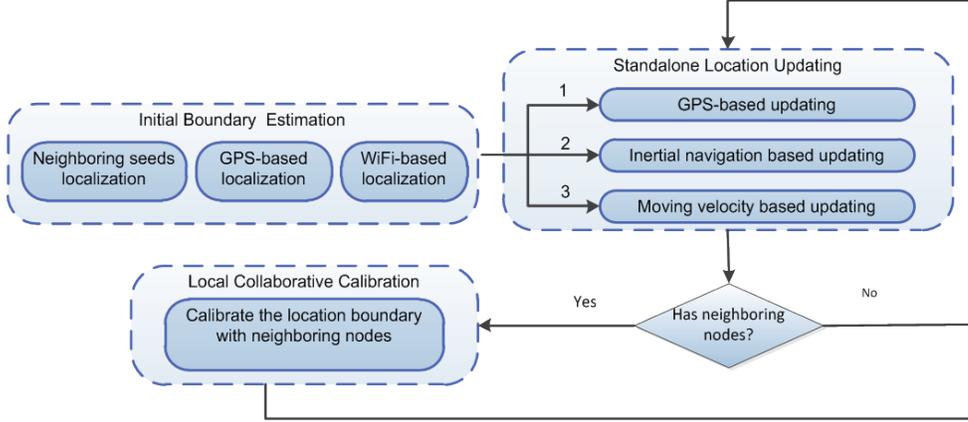


Figure 3: The work flow of MBL

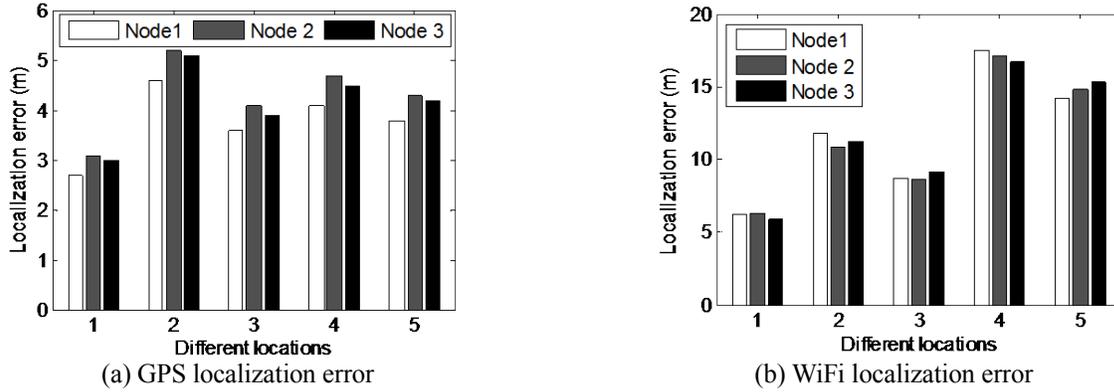


Figure 4: Indoor localization error using GPS and WiFi

### III. LOCALIZATION USING MBL

In this section, we present the details of MBL design. It mainly consists of three phases: *initial boundary estimation*, *standalone location updating* and *local collaborative calibration* as shown in Figure 3. In the next three subsections, we elaborate on the design of these three phases respectively.

#### A. Initial Boundary Estimation

In the first phase of MBL, each mobile node (*e.g.* mobile phone) initially computes its possible location range. There are three kinds of location range estimation according to the different situations.

First, all the mobile phones confirm whether they have neighboring seeds. If so, they take the communication range of neighboring seed as their possible location boundary. If there are multiple neighboring seeds, the boundary is the overlapping region.

For the type II and type III mobile phone without neighboring seeds, they check their GPS status first. If it is available, they may obtain their location by GPS directly. In our experiment, when the users stand at the window, the

GPS localization error is relatively low. We use three different mobile phones with GPS to evaluate location performance at five different windows as shown in figure 1. Figure 4(a) is the evaluation results. The mobile phones have different location accuracy at different positions due to multipath errors and other effects. It is delighted that the GPS localization error is less than 5m with the aid of other information such as the construction layout.

For the mobile phones without location information getting from GPS and neighboring seeds, they can only estimate their initial locations based on WiFi. In general given “enough” distance constraints between APs and mobile devices, it is possible to establish all their locations in a relative sense. Ideally, the RSSI and distance meet the log normal shadowing model.

$$P(d) = P(d_0) + 10 \times \eta \times \log \left( \frac{d}{d_0} \right) + X_\sigma \quad (1)$$

where  $P(d)$  denotes the reduction in received signal strength after propagating through a distance  $d$ ,  $P(d_0)$  stands for the path loss at a short reference distance  $d_0$ ,  $\eta$  is the path loss factor (also named signal propagation constant), and  $X_\sigma$  is a

random environment noise following  $X \sim N(0, \sigma_x^2)$ , according to the empirical knowledge reported in [16, 17].

However, the mapping between the RSSI and the distance is actually very uncertain in a real indoor environment caused by the radio interference. In our experiment, the WiFi-based localization has error between 5m and more than 17m at five different positions as shown in figure 4(b).

In general, the initial boundary estimation gives a rough estimate of the initial location range. The localization accuracy will be iteratively improved through the second and third phase.

### B. Standalone Location Updating

*Standalone location updating* utilizes the temporal-spatial stability of the movement to locate mobile users. There are three kinds of updating mechanism.

#### 1) GPS-based Updating

For the type II and type III mobile phones, they check the availability of GPS first in the *standalone location updating* phase. If so, they update their locations through GPS function. If not, type III mobile phones choose the inertial navigation based updating mechanism to obtain mobile users' movement trace. Type I and II mobile phones use *moving velocity based updating* mechanism.

#### 2) Inertial Navigation based Updating

Inertial navigation uses mobile phones with built-in sensors (i.e. gyroscope and accelerometer) to capture user's movement trace.

Gyroscopes measure the angular velocity of mobile phone in the inertial reference frame. By integrating the angular velocity, each mobile phone's current orientation is known based on the original orientation. Accelerometers measure the linear acceleration of mobile phone in the inertial reference frame. Through measurement of both the current angular velocity and linear acceleration of the mobile phone, it can determine its linear acceleration. Performing integration on the inertial accelerations, the mobile phone can estimate its inertial position using the correct kinematic equations. There are a lot of works in this field; therefore, it unnecessary gives more details.

As analyzed in section 2.2, the gyroscope and accelerators cannot get a favorable effect independently. All inertial navigation systems suffer from the integration drift: small measurement errors in acceleration or angular velocity may lead to progressively larger errors in velocity, which are compounded into greater errors in location finally. Since current location is calculated based on the previous location and the measured acceleration and angular velocity, these errors are cumulative and increase roughly through time.

We design a hybrid posture estimation method to take the absence of drift from gyroscope and the smoothness

from the accelerometer. The idea is to use multiple Kalman filter to achieve different kinds of sensor fusion.

In order to get high performance, data obtained from each sensor require transformations before being sent to the Kalman filters. Moreover, sensor measurements also require coordinate transformations to reduce the number of filters. For instance, the accelerometer has to be corrected with the known orientation of each mobile user. All the transformations run outside of the filters. Based on these characteristics, our Kalman filter models can be reduced to the simplest form,

$$l(k) = l(k-1) + v(k) \cdot dt + a(k) \cdot dt^2/2 \quad (2)$$

where  $l$  is the location of each node,  $v$  denotes the velocity,  $a$  is the acceleration and  $dt$  is the time interval between iterations.

Sensory data acquisition is done at different rates on the various sensors, and our sensor fusion strategy takes that into account by switching models according to what new data is available. Each filter contributes to the global estimate in a way inversely proportional to its error covariance matrix. Let  $X_1$  be the estimate from filter 1,  $X_2$  the estimate from filter, and  $P_1$  and  $P_2$  their respective error covariance matrices, the global fused estimate  $X_g$  is given by Equation 3.

$$X_g = \frac{X_1/P_1 + X_2/P_2}{1/P_1 + 1/P_2} \quad (3)$$

The smaller the error covariance of an estimate is, the larger it contributes to the global estimate. However, the random movement of users may bring the accumulated errors of inertial. The estimated error must be constantly corrected by input from some other location information. Each node exchanges its location information with its neighbors in each time slot. These multiple location data can also use Equation 3 to filter the noise and get relative accurate location.

#### 3) Moving Velocity based Updating

For the type I or type II mobile phones unable to obtain good GPS signs, they update their positions according to the location range estimated last time instance and their maximum moving speed  $v_{max}$ . Let  $S_t^i$  denote the location range of mobile phone  $i$  at time  $t$ . Since displacement of a user is a continuous process, it could not exceed a regular threshold in a fixed time slot. According to temporal-spatial stability of the movement,  $S_{t+1}^i$  can be computed as the amplified  $S_t^i$  at the range of  $v_{max}$ . For example, if  $S_t^i$  is a circle with a radius  $R$ , the  $S_{t+1}^i$  will be the concentric circle of  $S_t^i$  with a radius  $R + v_{max}$ .

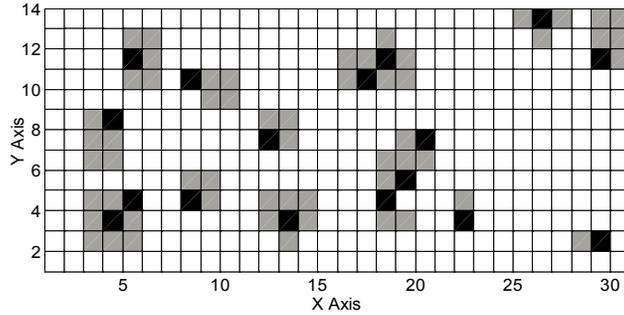


Figure 5: Localization results of MBL

### C. Local Collaborative Calibration

Local collaborative calibration is by taking advantage of the neighborhood relativity of mobile users to filter the impossible locations.

If a mobile phone has some neighbors, it should be in the overlap of these neighbors' radio range including both neighboring seeds and ordinary neighbors. Thus each mobile phone's possible radio range should be estimated before filtering. The mobile phone estimates its radio range  $R_i$  according to  $S_i$  and  $r$ . Each mobile phone computes overlap region between its locations set  $S_i^i$  and neighbors' radio range  $R_i^j$  as its new locations set  $S_i^i$ . That is,

$$S_i^i = S_i^i \cap R_i^j, \text{ all neighbors } j. \quad (4)$$

The second and third process will be cyclically done automatically and continuously, until the possible location set  $S_i$  is lower than a threshold.

## IV. PERFORMANCE EVALUATION

We have implemented MBL with InSpace. The performance of MBL is evaluated through real experiments as well as large scale simulations. For comparison, we have also implemented four existing localization approaches, namely Centroid [18], MCL [9] MSL\* [11] and EZ [13].

### A. Experiments on Real indoor System

We use twenty mobile phones and five PDA installed Windows Mobile 6.5 OS to evaluate the localization performance. Users carry the mobile devices walk around the rooms, and randomly choose their destinations and speed of movement. There are twelve seeds with BLE and six APs distributed in the rooms as shown in Figure 1.

To facilitate the calculation and evaluation, we divide the experiment area about 24m\*10m into a number of grids of 80cm\*80cm. We have collected the localization results of all the five approaches.

The accuracy of location estimation is the key metric for evaluating a localization approach. It is computed as follows:

$$\text{Error} = \frac{1}{n} \sum_{i=1}^n \|e_i - l_i\| \quad (5)$$

where  $l_i$  and  $e_i$  denote the real location and the estimated location of the  $i$ -th node respectively. For MBL,  $e_i$  is represented by the location of estimated range center, since it estimates a node's possible location range instead of a concrete location.

Furthermore, we introduce two additional metrics for a more in-depth evaluation of MBL. That is the size of estimated location range and its coverage ratio. The size of estimated location range of  $i$ -th node is represented by the range radius  $A_i$ . The coverage ratio is the percentage of nodes' real locations covered by their estimated range, denoted by  $\delta$ . Obviously, the small location range and high coverage ratio indicates the high performance of MBL.

#### 1) Overall localization result of MBL

In this experiment, there are seventeen persons walking randomly in the area with mobile phones in their hands for five minutes. Figure 5 shows the localization result of MBL. The black grids stand for the true locations of all the persons, and the gray grids are the estimated locations using MBL. There are some interesting findings. One is that almost all the groups of gray grids cover the black grids, and most black grids around the center of the groups. The coverage percentage  $\delta$  is 94.1%, and the mean range radius  $A$  is about 1.3m. It indicates that MBL has relatively high localization accuracy in this scenario. The other is that the number of grad grids in different groups is different. The mobile phones close to the door always have high precise position. That is because there are seeds deployed around the door to provide more accuracy location information. The nodes close to the windows also have a desirable outcome, which is consistent with the result in Figure 4(a).

#### 2) Comparison among Approaches

Figure 6 shows the mean localization error for 17 nodes and 25 nodes. We make the following observations. First, the number of nodes has more influence on localization accuracy than movement speed for MBL, Centroid, and MSL\*. That is because these methods all more or less use the neighboring nodes to estimate locations. The number of nodes can provide more location information. Second, EZ has relatively stable errors. That is because EZ is use the

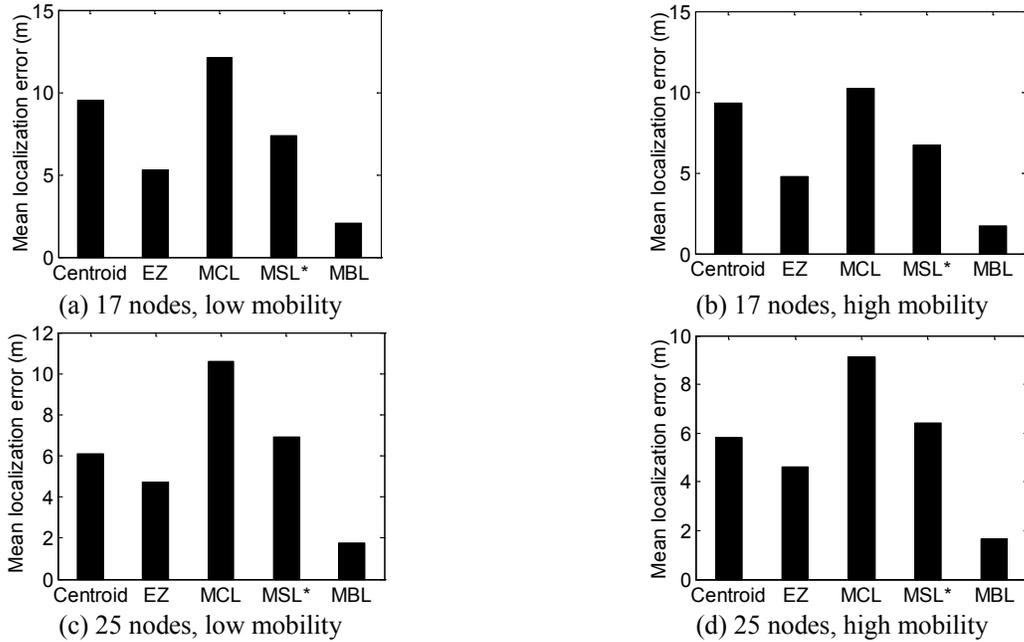


Figure 6: Comparison among approaches

RSS measurements from APs to estimate location of mobile devices. It does not depend on the node density and movement speed too much. Third, MCL is more sensitive to movement speed than other approaches. That is because high mobility provides each node more chance to directly get location information from seeds. Finally, MBL localization approach significantly out-performs the other approaches in four kinds of situations. It is different treatment for different kinds of conditions and let each node for maximum effect update its location range independently. Each neighboring node exchanges location information to filter impossible locations to get a good localization performance.

### B. Simulation on Large Scale Networks

We have also carried out extensive simulations to evaluate the performance of MBL comparing with other approaches. We examine the location accuracy of MBL by tuning a series of parameters such as movement speed, node density, and seed density.

The simulation results of Centroid, MCL, MSL\* and EZ are also presented for a more comprehensive comparison under various network configurations. In the simulations, nodes are randomly deployed in a 100m\*100m square region. The network and node parameters are described as follows:

- Moving speed ( $v$ ), the moving distance per time interval. Each node's moving speed is randomly chosen from  $[0, v_{max}]$ .

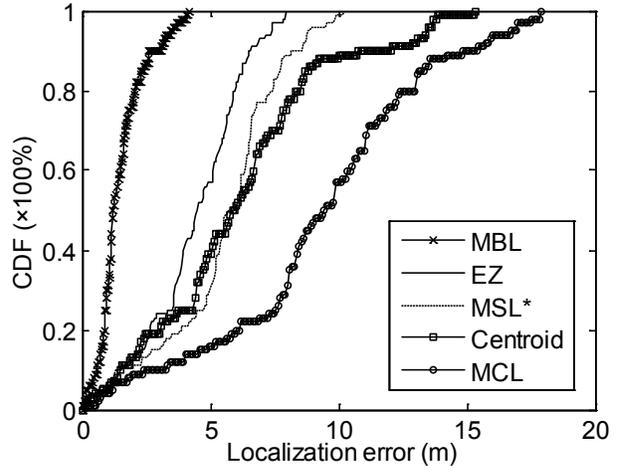


Figure 7: Localization performance

- Node density ( $n_d$ ), the average number of one hop neighboring nodes.
- Seed density ( $s_d$ ), the average number of one hop neighboring seeds.

We use a modified version of random waypoint mobility model [19] for both nodes and seeds adopted by Hu and Evans. We assume that the type I mobile phones have no knowledge about their velocity and direction, but know the maximum moving speed  $v_{max}$ . In this model, a node randomly varies speed and set pause time during each movement to prevent decay of average speeds in the random waypoint model [19, 20].

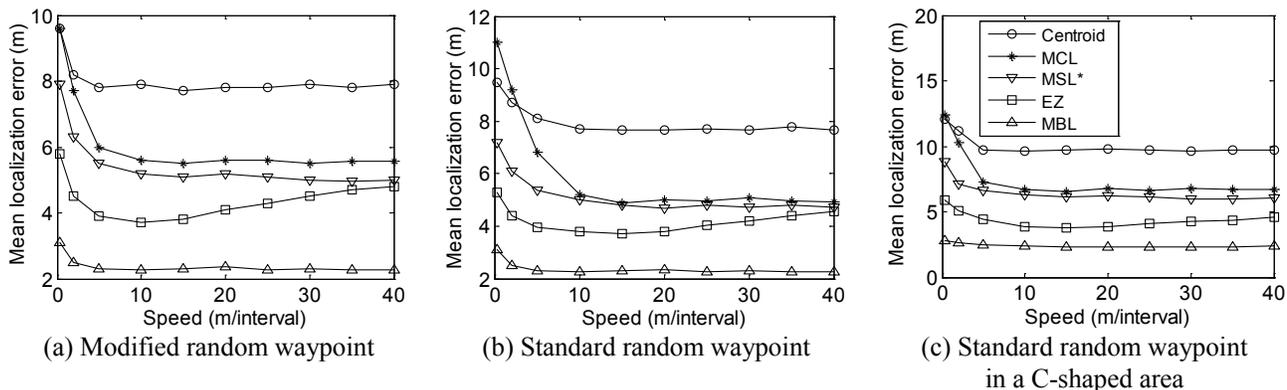


Figure 8: Comparison of different localization approaches using random waypoint models.

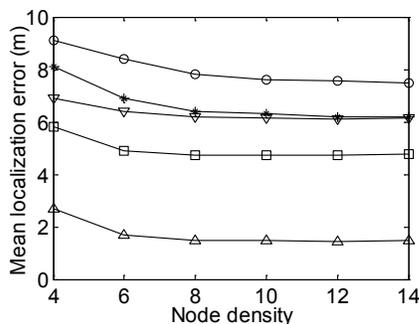


Figure 9: Impact of node density

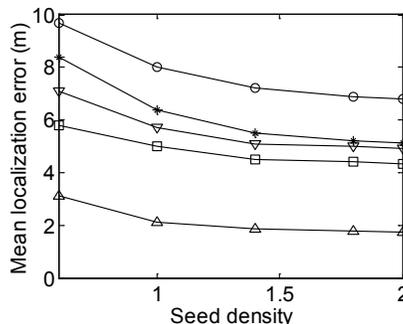


Figure 10: Impact of seed density

### 1) Accuracy

Location accuracy is the most important evaluation criterion for a localization algorithm. Figure 7 plots the cumulative distribution of the localization errors using the five approaches. It is easy to see that MBL performs better than other four approaches.

Using MBL, 100% of the mobile nodes have errors of less than 5 meters, while about 80% of them have errors less than 2 meters. MBL is different treatment for different conditions and let each node for maximum effect to estimate its location range. For MBL, the nodes without assist of GPS, neighboring seeds and inertial navigation can still get location information from its ordinary neighbors to filter impossible locations. Using EZ, at most 20% of nodes have errors less than 2 meters. It is also interesting to see that MBL achieves the most consistent performance among the five approaches. The average localization errors of five techniques are 1.9m, 4.4m, 5.4m, 6m and 9.3m.

### 2) Moving Speed

Figure 11 compares various localization schemes by varying the amount of noise. Figure 8(a) shows the results under the default network configuration, Figure 8(b) shows the results under higher mobility, and Figure 8 (c) shows the results under lower node density. We make the following observations. First, as we would expect,

increasing noise degrades the accuracy of all the localization schemes. Among them, the error in Centroid increases slowest, because it estimates its location as the center of all neighboring seeds and is not affected significantly by measurement errors. Similar effects were observed in [22]. Second, MBL continue to yield the lowest errors under all noise values. That is because MBL utilizes the temporal-spatial stability and neighborhood relativity of mobile users. It exploits more associated information to reduce the effects of noise. Finally, increasing the maximum speed from 10 m/interval to 30 m/interval slightly degrades the accuracy of various schemes. Among them, MSL\* is affected the most, because it uses the maximum speed to generate feasible node positions during the next intervals and location uncertainty increases with mobility.

### 3) Node Density

Figure 9 compares the effect of node density on estimate error for different localization approaches. In this experiment, we keep the number of seeds constant in the network and tune the node density by changing the number of nodes. We set  $s_d = 1$  and  $v_{max} = 0.2r$  where most algorithms have good performance.

As we would expect, the accuracy of all the schemes degrades as the node density decreases due to fewer location constraints. In MSL\*, high node density provides

more first-hop and second-hop neighbors to communication with each node, and therefore location accuracy is improved. In MBL, as the number of nodes goes up, the estimate error continuously drops. That is because when node density is high, each node has more direct neighbors to collaboratively filter the impossible locations.

#### 4) Seed Density

We further vary the seed density by fixing the area to the default size as before and changing the number of seeds. Figure 10 summarizes the results. As we would expect, all the localization schemes benefit from increasing seed density.

The accuracy of MCL is considerably influenced by seed density. The estimate error drops fast as seed density increases. In MCL a node filters the impossible locations based on location information from seeds, so increasing the number of seeds provides a node with more location information of them. In MBL and MSL\*, a node filters the impossible locations utilizing information including both nodes and seeds. When node density exceeds a threshold, the number of seeds does not influence the location accuracy too much. Moreover, MBL significantly out-perform the other schemes.

## V. RELATED WORK

We classify the related work into the following two categories: (i) localization in static wireless networks, (ii) localization in mobile networks

### A. Localization in Static Wireless Networks

The existing work on localization in static wireless networks falls into two main categories: range-based and range-free localization.

Range-free approaches, such as APIT [7], and DV-HOP [19], mainly rely on connectivity measurements (for example hop-count) from landmarks to the other nodes. In Centroid, seeds broadcast their positions to their neighbor nodes that record all received beacons. Each node estimates its location by calculating the center of all seeds it hears. In APIT, each node estimates whether it resides inside or outside several triangular regions bounded by the seeds it hears, and refines the computed location by overlapping the regions the nodes likely reside in. As an alternate solution, DV-HOP only makes use of constant number of seeds. Since the quality of localization is easily affected by node density and network conditions, range-free approaches typically provide imprecise estimation of node locations.

Range-based approaches measure the Euclidean distances among the nodes with certain ranging techniques and locate the nodes using geometric methods, such as TOA [8], TDOA [20], [22], and AOA [3], [18].

TDOA estimates the node locations by utilizing the time differences among signals received from multiple senders. AOA [21] allows nodes to estimate the relative directions between neighbors by setting an antenna array for each node. All those approaches require extra hardware support. TOA obtains range information via signal propagation times. RSSI-based range measurements are easy to implement and popular in practice. Empirical models of signal propagation are constructed to convert RSSI to distance [25]. The accuracy of such conversions, however, is sensitive to channel noise, interference, and multipath effects. Besides, when there are a limited number of landmarks, range-based approaches have to undergo iterative calculation processes to locate all the nodes, suffering significant accumulative errors [14]. More recent proposals mainly focus on the issue of error control and management [13], [16]. J. Liu *et al.* [14] propose iterative localization with error management. Only a portion of nodes are selected into localization, based on their relative contribution to the localization accuracy, so as to avoid error accumulation during the iterations. Similarly, H.T. Kung *et al.* [11] propose to assign different weights to range measurements with different nodes and adopt a robust statistical technique to tolerate outliers of range measurements. The noisy and outlier range measurement can be sifted by utilizing the topological properties of a network [10].

### B. Localization in Mobile Networks

No approaches mentioned above consider the scenario that sensors move freely. Compared to significant related work on static network localization, there are considerably fewer works on localization in mobile networks. Bergamo *et al.* [22] are the previous research to perform localization in mobile sensor network. They assumed that network includes two fixed seeds and mobile nodes can accurately measure the received power strength. The location is estimated by means of triangulation. Tilak *et al.* [23] showed that applications of mobile sensor network are extensive. In addition, they investigate the tradeoff between energy and accuracy: a frequent positioning reduces error but increases energy consumption. Hu *et al.* [24] used Monte Carlo Localization (MCL) to estimate node location. Each node maintains samples which are probabilistic distribution of its location. A node estimates new possible locations based on previous locations and maximum velocity, and then removes samples that are inconsistent with new observations. There is a limiting condition that node must be one or two-hop neighbor of certain seeds. DRL [25] proposed by Hsieh *et al.* is an improved algorithm of DV-Hop. Each mobile node locates itself by regular triangulation and other reference information. Then seeds update the parameters provided for other nodes, which increases network load. In addition, if nodes move in a

straight line or are not in overlay area of seeds, there will be massive calculation.

## VI. CONCLUSION

In this paper, we introduce our vision for a ubiquitous indoor positioning system. Our approach MBL is based on mobile phones, which are ubiquitous computing and sensing devices. We share our real-world experience, design, and evaluation of mobile phone based localization with InSpace, a pervasive computing system with various wireless devices to provide intelligent services to users. We analyze real mobility traces and find that they exhibit temporal-spatial stability and neighborhood relativity of mobile users. Motivated by this observation, we develop a novel localization approach. Our design, called MBL, applies an iterative process to constantly exploit the associated information during each time interval. In the future, InSpace will continue the research and development in pervasive computing. We plan to mix our localization approach in more practical applications.

## ACKNOWLEDGMENT

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