M-SHOW:A SYSTEM FOR ACCURATE POSITION ESTIMATION IN MULTI-FLOOR BUILDINGS

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Abstract: This paper presents M-Show, a Wireless LAN based system for locating users inside multi-floor buildings. It makes improvements in the sampling, processing and storing of empirical signals to previous studies, and builds a Fuzzy Empirical Signal Model that gives more credible description of signal distribution. By dividing the map into different sized Intelligent Areas (iAreas), M-Show is able to achieve alterable positioning granularity within the same map. It also unprecedented adopts AP Close Range Pre-Locating strategy to quickly locate the users inside a certain small scope around an AP. In addition, since statistical calculation methods are inefficient in distinguishing vertically overlapping positions on different floors, which is not tackled in previous locating systems, we introduce the Fluoroscopy to rectify the locating result of probability calculation. M-Show is deployed in Shanghai Science and Technology Museum, and experimental results show that with reduced average position query time and lower computation cost, M-Show achieves a high locating accuracy of 93% probability within 3 feet around the user's actual position.

1 INTRODUCTION

As mobile computing devices and deployment of local area wireless networks (WLAN) mushroom, context-aware computing and service is becoming practical. Applications that provide services related with user locations, namely the Location-Based Services (LBS), have gained growing popularity and are developed increasingly complicated. Examples of these services include *map in the palm*, which displays on a cell phone or PDA screen the map of the region around the user, and *intelligent exposition tourist*, which intermittently locates the user and guides him/her through the exhibition.

In this paper, we focus on methods of estimating accurate user position in multi-floor buildings with WLAN. We studied the WLAN based locating systems developed up to now, made improvements to some methods presented, and put forward our own novel solutions against new challenges.

The challenges that motivate us to develop M-Show include:

1) Are empirical signal models creditable?

In most WLAN based locating systems developed by now, an empirical signal model is built as a paradigm to which instant signals are compared with (P.Krishnan et al., 2004). The idea is feasible in less demanding applications. However, since radio signal of WLAN is easily blocked or reflected by shutting doors, closing windows, and even moving human bodies, signal distribution is constantly changing (Andrew Howard et al., 2003). A one-off sample of a static position only represents signal distribution of the moment; as time elapses, signal distribution changes and the previous sample is no longer authentic. Thus, it is essential to find a way of signal sampling and storage to help eliminating the influence on system performance cause by the fluctuation of signal.

2) How to locate users in a multi-floor building?

Many systems have realized user locating on a single floor (Paramvir Bahl et al., 2000). But users move freely in buildings. When it comes to locate a user who roves in a multi-floor building, are the old methods efficient in settling new problems? How should maps be organized for the convenience of empirical signal storage? As the total area of system deployment doubles and redoubles, how can we eliminate the growth in the size of Empirical Signal Model without loss in performance?

3) Are there crosscuts in positioning?

Among all previous systems, the probability calculation has been the most popular method for it complies with the instable nature of radio signal.

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However, the calculations can become highly complicated if a good accuracy is to be achieved, and consequently the computation expense rises and time of location query extends. Can we build a crosscut in positioning, by which we can avert from the arduous probability calculation every now and then? By more intensive study of the rules of signal propagation, can we find a method to quickly locate the users in special areas, just like "finding the islands in an ocean"?

2 RELATED WORK

Techniques used to track user location include GPS (P.Enge et al., 1999), Mobile Cellular positioning (S.Tekinay, 1998), infrared ray based locating (R.Want et al., 1992), ultrasonic based locating (N.B.Priyantha et al., 2000), and Wireless LAN radio signal based locating (Paramvir Bahl et al., 2000). GPS is excellent for outdoor user locating, but since satellite signal is easily blocked by walls, GPS is barely efficient for indoor user locating. Mobile Cellular positioning has been widely used in cell phone user tracking, but it can only tell the approximate range of a user. Infrared and ultrasonic signal based systems can achieve a higher accuracy, but they require special sensor modules to work which makes them expensive to deploy. Up to now, Wireless LAN radio signal is the most popular technique adopted in indoor position estimation systems, because it can achieve good accuracy, and the prevalence of Access Points (APs) and mobile computing devices with WLAN access makes it easy and inexpensive to deploy.

Many WLAN based location estimation systems have been put forward over the years. The following ones are generally considered typical and major.

RADAR (Paramvir Bahl et al., 2000) developed by Microsoft Research was the earliest system to use WLAN signal in indoor locating. It builds a radio map and searches the k-best-neighbour of the received signal, and the mean location of the k neighbours is regarded to be the most probable location of the user. The problem with RADAR is that its computation cost is high since it searches the whole radio map each time it does location estimation. And it does not give very high accuracy.

HORUS (M.Youssef et al., 2002) regards the strength of radio signal (rssi) as a statistical variable. Via Bayes probability calculation, HORUS gained a great advance over RADAR in accuracy. But a great number of signals need to be sampled to form the probability distribution formula, which makes HORUS exhaustive to deploy.

Complex Systems Computation Group of University of Helsinki (T.Roos et al., 2002) presented Ekahau, which does locating by building statistical model of WLAN radio signal. It studies the rules of signal propagation and builds signal attenuation models. Its performance is susceptible to changes of the environment because it fails to shield the instability of signal.

LOCATOR (A.Agiwal et al., 2004) gained better accuracy over RADAR and HORUS by making improvements in signal sampling and map clustering. But since LOCATOR simply divides map into uniform areas, computation cost raises significantly as the granularity of clustering increases.

3 M-SHOW

Our system for accurate in-building user locating, M-Show, works in two phases. Firstly, a Fuzzy Empirical Signal Model is built. It is a mapping between stored sets of signals and the real physical locations. It consists of radio signals of various APs and the location where the signals are sampled. In the second phase, instant signals are analyzed by our four steps and an estimated position is returned as the result. These two phases are described in greater detail in the following subsections.

3.1 Fuzzy Empirical Signal Model Building Phase

In this phase, a database is built that describes how wireless signal propagates in the physical space where Wireless LAN is deployed. It enables M-Show to estimate user's accurate position inside a multi-floor building as described in section 3.2. In the following subsections, how the map is fragmentized into Intelligent Areas (iAreas) is discussed, followed by the signal strength sampling strategy, and then the methodology adopted for marking an iArea with multiple sets of multiple signal strengths from various APs.

3.1.1 Fragmentizing Maps into iAreas

Consider the following scenario: a position estimation system is to be deployed on a floor of an office building, as shown in Figure 1. For the majority of the floor area, a positioning accuracy of 10 meters is demanded; in the two meeting rooms, 4 meter accuracy is required.

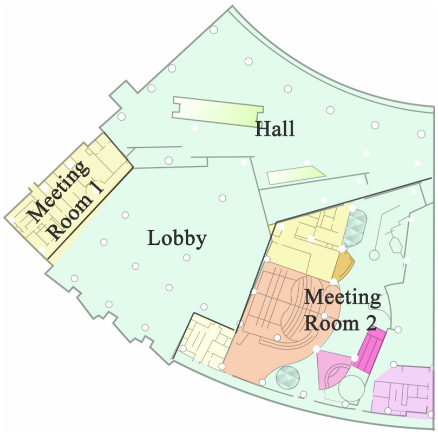

Figure 1: Map of the Office Building.

Consider adopting a traditional way of map clustering (A.Agiwal et al., 2004). The entire site is divided into 4-meter-diameter areas, as shown in Figure 2, to guarantee the highest positioning accuracy required, which is a notable waste of system computing power. Assume that the system rubs through anyhow; one day, the owner of the building decides to increase the accuracy of the two meeting rooms to 3 meters, so unfortunately the whole map will have to be re-divided into 3-meter-diameter areas and what's worse, the sampling and radio map building for the whole floor will have to be done all over again.

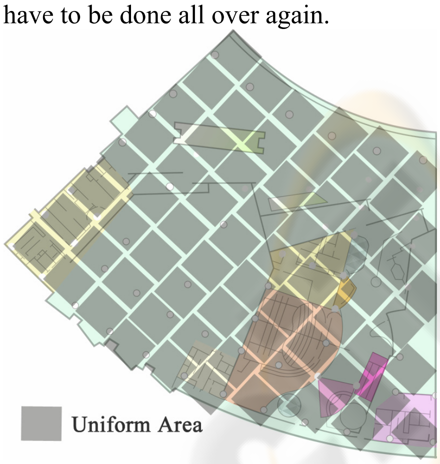

Figure 2: Map Clustered into Uniform Areas.

Now let's see what happens in the scenario if M-Show's way of map fragmentation is used. Firstly map of the floor is fragmentized into two kinds of Intelligent Areas (iAreas): the two meeting rooms are divided into 4-meter-diameter Smart iAreas, and the rest part of the map 10-meter-diameter Mega iAreas, as shown in Figure 3. Thus the required positioning accuracy is guaranteed and system computation power is put to best use. If accuracy of the two meeting rooms needs to be increased, we simply re-divide the two rooms into 3-meter iAreas and redo the empirical signal sampling in the two rooms.

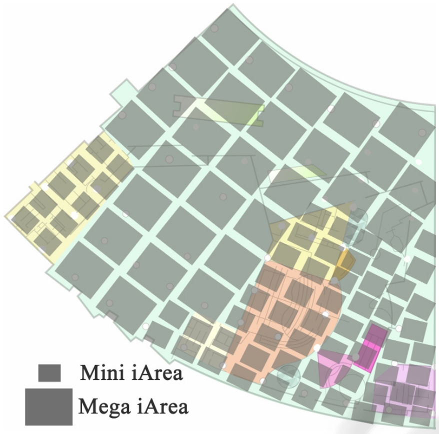

Figure 3: Map Clustered into iAreas.

How the map is divided into iAreas lies on the granularity of positioning requires, but the following are the basic rules:

1) An iArea should be on one layer of the map.
2) iAreas should not overlap each other.
3) Adjacent iAreas should border on each other.
4) An iArea is larger than area of AP Close Range.

3.1.2 Sampling Strategy

The radio signal of Wireless LAN is highly unpredictable and changeful due to the following reasons:

1) Radio signal strength changes according to the temperature, humidity and the moving of human body.
2) Radio signal reflects, refracts and diffracts during propagation indoors, which causes the "Multi Path Effect".

To avoid this feature being a bad influence on position performance, previous systems have used average value of samples (Paramvir Bahl et al., 2000). But mere averaging the samples is not sufficient. Figure 4 shows the signal of an AP sampled in 5000 times, with an interval of 1 second, from which we can see that the signal does not follow a particular mean strength. Thus M-Show adopted a novel sampling strategy, which includes:

1. All-Orientation Sampling

Signal is collected with the sampler facing each of the four orientations: the north, the west, the south and the east. Then by processing the signals via formula $\lg rssi_{Direction\_x} = \frac{\sum_{i=1}^{n} \lg rssi_i}{n}$, four figures are obtained denoting each of the four orientations on a certain location.

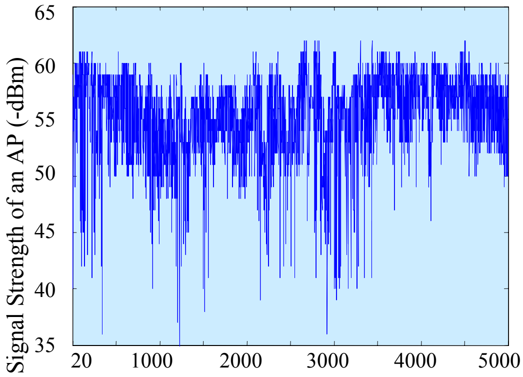

Figure 4: Fluctuation of Signal during 5000 times of Sampling.

2. All-Time Sampling

We collect signals on deliberately selected environmental conditions including: those with rainy, sunny, cloudy and snowy weather; those with dry, common and humid air; those with many peopling walking all over the place, several people moving and no people presents; with doors and windows open and with doors and windows closed. Signals collected are processed via the formula:

$$rssi_{TimeDiverse} = \frac{rssi_1 + rssi_2 + \cdots + rssi_n}{n} = \frac{\sum_{i=1}^{n} rssi_i}{n},$$

and all-time sample is obtained denoting the signal on a certain location through all status of the space possible.

3.1.3 Marking an iArea

Unlike previous systems where an area is marked with signals from several APs, M-Show mark an iArea with sets of AP signals. Firstly, we sample in different location of the iArea, towards different orientations, at different chosen times. Then, signals collected in an iArea are organized to form such a set: $\{\{(mac_{(E)\_APi}, \{rssi_{(E)\_APi\_j}\})\}_k\}$, where $(mac_{(E)\_APi}, \{rssi_{(E)\_APi\_j}\})$ presents the j empirical signals from APi, and $\{(mac_{(E)\_APi}, \{rssi_{(E)\_APi\_j}\})\}$ presents all signal sets of all APs observed in this iArea.

To mark an iArea in such a redundant way enables the system to be impervious to changes of weather, moving of human bodies, and distinction of user orientation. According to tests as described in section 4, M-Show's way of marking an iArea helps the system give better position estimation performance with even less computation expense.

3.2 Position Estimation Phase

In the position estimation phase, user's mobile terminal device periodically collects AP signals in format of $\{(mac_{(R)\_APi}, rssi_{(R)\_APi})\}$, and then the system estimates the user location in four steps as described in the following subsections.

3.2.1 AP Close Range Pre-Locating

Radio signal attenuates while propagation, as shown in Figure 5, according to the following law:

$Attenuation\ (d) = A_0 + \alpha log\ (d) + X_\sigma$ (Figure 3)

(d represents the distance between AP and the receiver, A_0 and X_σ are constants.)

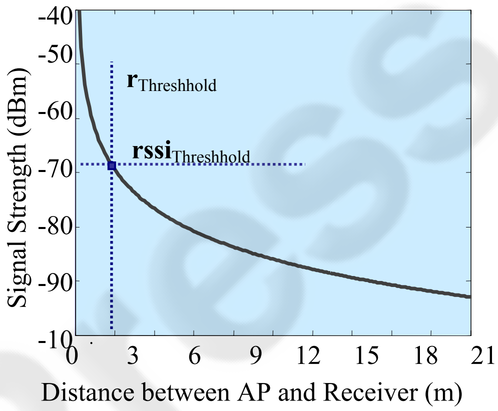

Figure 5: Signal Attenuation in Free Space.

An AP Close Range Threshold ($r_{Threshold}$) is an area around the AP in which signal does not follow a normal distribution. $r_{Threshold}$ of different APs vary according to their power and other environmental complications, its value commonly between 2 and 3 meters. $rssi_{Threshold}$ represents the average signal strength on the circumference of the Close Range.

Because AP's Close Range radius is smaller than an iArea, if we can ascertain a user's location in an AP Close-Range, we can also tell which iArea he/she is in. If we use $iArea_{(T)\_APi}$ to represent the iArea AP_i's Close Range lies in, the process of AP Close Range Pre-Locating can be described as:

```
FOR ALL MEMBERS IN {(mac(R)_APi, rssi(R)_APi)}
IF ∀j s.t. rssi(R)_APj ≥ rssiThreshold_APj
THEN RETURN Area(T)_Apj
```

3.2.2 Empirical Signal Filtering Strategy

The multiple sets of signals M-Show uses to mark an iArea represents signals a Mobile Terminal is likely to receive under ALL environmental conditions: in different weathers, with doors open and close, with people moving all over or no people at all, and the user facing north or east…and so on. However, as far as a certain query of position is concerned, not all the signals stored need to be used in calculation. In order to cut down computation cost, An Empirical Signal Filtering Strategy is adopted.

We use $\{(mac_{(T)\_APi}, rssi_{(T)\_APi})\}$ to represent signal sets collected instantly by Mobile Terminal, $U_{empi}=\{\{(mac_{(E)\_APi}, \{rssi_{(E)\_APi\_j}\})\}_k\}$ to represent the empirical signals stored in Fuzzy Empirical Signal Model, and $U_{prob}=\{\{(mac_{(U)_APi}, \{rssi_{(U)_APi_j}\})\}_k\}$to represent the set of signals which are screen out by Empirical Signal Filtering Strategy. Let U_{prob} initially equals U_{empi}, and Empirical Signal Filtering Strategy can be described by the following steps:

1. To eliminate empirical signal sets of the APs who's signal is not received by Mobile Terminal.

```
IF ∀ x,y s.t. mac_APx∈{mac_(T)_APi}&&
   mac_APx∉{mac_(E)_APi}y
THEN U_prob = U_prob -
   {(mac_(E)_APi, {rssi_(E)_APi_j})}y
```

2. To select one set out of all empirical signal sets of each AP that is with the minimum vector distance towards the observed signal set.

```
FOR EACH {(mac_(U)_APi,{rssi_(U)_APi_j})}
       IN U_prob
 AND FOR EACH mac_(U)_APi IN {mac_(U)_APi}k
   FIND |rssi_(R)_APi-rssi_(U)_APi_z|
     =min {| rssi_(R)_APi-rssi_(U)_APi_j |},
    (j=1 to SizeOf {rssi_(U)_APi_j}k )
   THEN{(mac_(U)_APi,     {rssi_(U)_APi_j})}k
       ={(mac_(U)_APi, {rssi_(U)_APi_j})}k
         - (mac_(U)_APi,{rssi_(U)_APi_j})
         + ( mac_(U)_APi, rssi_(U)_APi_z)
```

3.2.3 Joint-Probability Calculation

At a static point outside AP Close Range, the signal follows the normal distribution. The concept of computing Joint-Probability is to aggregate all probabilities of the user's presence in each iArea and to select the one iArea with the highest probability. To do this, we take the following three steps:

1. To compute the Singular Probability Set of each iArea

Here we use $\{\{(mac_{(U)\_APi}, rssi_{(U)\_y\_APi})\}_j\}$ to represent $iArea_y$'s empirical signal set obtained by Empirical Signal Filtering. If the signal received from AP_x is $rssi_{APx}$, the probability of the user being in $iArea_y$ is:

$$\mathrm{Prob}_{xy}(j) = \frac{1}{\sigma\sqrt{2\pi}} \cdot \exp\left(-\frac{(rssi_{APx} - rssi_{(U)\_y\_APx\_(j)})^2}{2\sigma^2}\right)$$, σ^2 is the variance of AP_x's signal in $iArea_y$.

If Mobile Terminal fails to receive signal from AP_x (or the signal is simply to weak to be sensed), M-Show adopts a compensatory value called Not-Null-Probability as a substitute of the singular probability. The Not-Null-Probability of AP_x's signal in $iArea_x$ is the possibility that Mobile Terminal can receive AP_x's signal inside $iArea_x$. For example, among all signal sets collected in $iArea_x$, 30% of which contain AP_x's signal, then the Not-Null-Probability of AP_x's signal in $iArea_x$ is 0.3.

2. To calculate the Joint-Probability of each iArea

By calculation of each iArea's singular probability set, a Singular Probability Matrix is formed, as shown in Figure 6.

	$Area_1$	$Area_2$	…	$Area_n$
AP_1	$\{Prob_{11}(i)\}$	$\{Prob_{12}(i)\}$	…	$\{Prob_{1n}(i)\}$
AP_2	$\{Prob_{21}(i)\}$	$\{Prob_{22}(i)\}$	…	$\{Prob_{2n}(i)\}$
…	…	…	…	…
…	…	…	…	…
AP_m	$\{Prob_{m1}(i)\}$	$\{Prob_{m2}(i)\}$	…	$\{Prob_{mn}(i)\}$

Figure 6: The Singular Probability Matrix.

We compute the Joint-Probability of an iArea by multiplying each element of its Singular Probability Set:

$$\mathrm{Joint\_Prob}_{x}(i) = \prod_{j=1}^{j\le m} \mathrm{Prob}_{jx}(i)$$. Find s, t, so that

$$\mathrm{Joint\_Prob}_{Area_s}(t) = \max\{\mathrm{Joint\_Prob}_{Area_j}(k)\}$$,

(s,j∈{1 to n};

t,k∈{1 to SizeOf{$\mathrm{Joint\_Prob}_{Area\,j}(i)$}}), then $iArea_s$ is the position estimation result of Joint-Probability Calculation.

3.2.4 Fluoroscopy: Shadow iAreas Distinguishing Strategy

When deploying a locating system in a multi-floor building space, the problem we call "Shadow iArea Problem" arise. Shadow iAreas are two or more iAreas that do not lie on the same floor of the building, but vertically superpose each other. Because of their geographical being, it is difficult for the system to perceive distinctly between them in that:

- signals received in these iAreas are mostly from the same APs;
- signal of a certain AP received in these iAreas are close to one another in value.

Joint-Probability Calculation can be inefficient in distinguishing Shadow iAreas for the calculation result represents an estimation in which each AP's signal contributes the same weight of effect, it is weak in capturing subtle difference of AP's signals received in Shadow iAreas.

Thus M-Show adopts a remedy strategy called the Fluoroscopy to track down the nuance. By our observation, there is always at least one AP's signal that differs distinctly in Shadow iAreas. In Empirical Signal Model Building Phase, we pay special attention to these APs and mark them as "Fluorescence AP" of the Shadow iAreas. After Joint-Probability Calculation, we check whether the result iArea is a Shadow iArea. If so, all iAreas that forms its shadows are listed, and signals of their Fluorescence AP stored in the Empirical Signal Model is compared with the signal strength actually received by Mobile Terminal. Finally, the iArea with the closest Fluorescence AP signal is selected and returned as the final position estimation result.

4 SYSTEM EVALUATION

In this section, the setup of M-Show is described, including the devices' setup and choosing of their models, along with the enumeration of system's parameters. A detailed system performance evaluation is offered in comparison with other WLAN based position estimation systems.

4.1 System Layout

M-Show System is part of the Shanghai Science and Technology Museum construction project. M-Show deployed Wireless LAN on the 2nd and 3rd floor of the museum, with a total site area of 18,000 m^2.

We adopt iPAQ 2210 Personal Didigital Assistant as the Mobile Terminal device. SanDisk WiFi-128M SD Card (-83dBm, 11Mbps) is used in iPAQ to collect Radio Signal Strength, and it also works as an extension of iPAQ's limited memory. AboveCable ACAP2010-11/H and ACAP1800-LS are our chosen AP models. APs are placed on roofs, and horizontal distance between two neighbour APs is 7-20 meters on average.

The Mobile Terminal receives 10 to 30 AP's signals in one scan. We choose the top 16 rssi to do Empirical Signal Filtering (i.e., n=16). According to experimental analysis, $r_{Threshold}$ of an AP is 2 meters. The site map is divided into iAreas of two sizes, with diameters of 3 meters and 6 meters.

My Position on Map

Figure 7: Snapshot of M-Show's Mobile Terminal Screen.

Figure 7 is the screen display of Mobile Terminal when M-Show estimates the user position. The square on right-top of the screen is a map of the museum section where the user locates, and the red dot represents his/her current position. The main part of the screen is a more detailed map of only a few meters around the user.

4.2 Performance Evaluation

In this section, a performance comparison is made between M-Show and other Wireless LAN based position estimation systems.

We compared performance among M-Show and analogous WLAN based systems by estimating the average times of computing of the three systems. The test is done on the premise that they are deployed on the same region of a floor, and they give the same positioning accuracy. M-Show clusters the map of the region into two kinds of iAreas: the 3-meter Smart iAreas and the 6-meter Mega iAreas, with the ratio of 6:4. As for LOCATOR and RADAR, the map is divided to 4-meter areas. The numbers in Figure 8 are average values of the 300 times tests we take, and the times of computing for each position query is the synthesis of computing times each system takes to do the database searching and result revising.

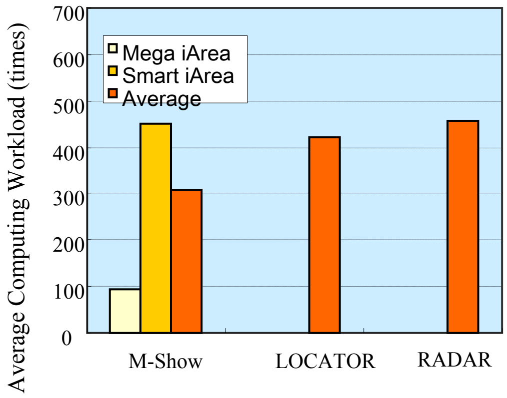

Figure 8: Average Times of Computing in Various Systems.

From the darkest bars shown in Figure 8, we can see the average times of computing M-Show needs to process a position query is significantly below those of other systems. This is credited to the Intelligent Area Clustering that M-Show has adopted. We can see from the central bar of M-Show that although the times of computing needed to locate users in Smart iAreas is slightly higher than the other systems, but to be fair, the Smart iAreas is originally of a higher granularity than the others. More importantly, the performance of M-Show in locating users within Mega iAreas is especially commendable, that it takes only less than 100 times of computing. This is attributed to the Empirical Signal Filtering strategy adopted by M-Show, by which M-Show is able to easily throw off the less possible iAreas and commit to the probability calculation and comparison among the most probable ones.

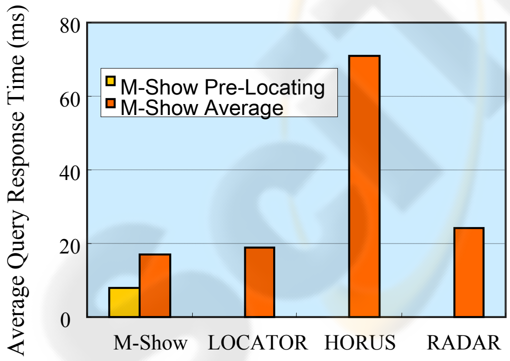

Figure 9: Average Query Processing Time of Various Systems.

The performance of the four systems is evaluated in terms of the time it takes each of them to response to a position query. To be fair, we configured the four systems to the approximately the same positioning accuracy and system load. The four systems are run under same hardware settings, and we record the time a query for position comes in and the output of the result, and time elapsed between them is recorded. The result shown in Figure 9 is an average of 300 times test and record. And for 102 times among the 300 times of query, the user is located to AP Close Range. We can see from the darker bars shown in the picture, that the average time M-Show uses to process a position query is shorter than LOCATOR and RADAR, and significantly shorter than HORUS. And thanks to the AP Close Range Pre-Locating strategy M-Show adopts, when the user is standing right near an AP, the time taken for M-Show to do the locating is remarkably shorter than the other systems.

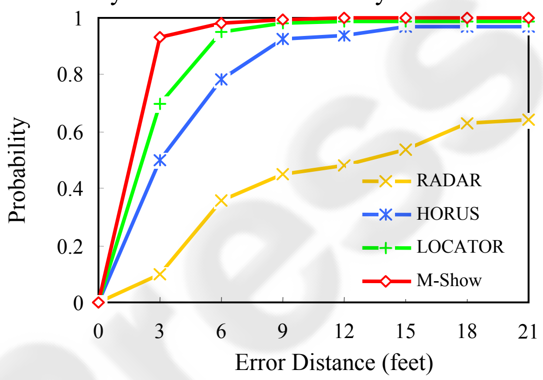

Figure 10: Error Distance CDF in Various Systems.

Finally, a comparison of the cumulative distribution function (CDF) among the four systems is provided. It needs to be mentioned that because the other systems measure their accuracy in feets, M-Show also altered its measuring unit to feets. Since M-Show estimates the iArea of user location instead of a single point, we regard the error of locating is half the diameter of an iArea. As observed from Figure 10, M-Show gives 93% accuracy to within 3 feet while LOCATOR gives 70% accuracy, HORUS 50% and RADAR 10%. Within 6 feet range, M-Show gives a 97% accuracy while the figure for LOCATOR, HORUS and RADAR is 95%, 78% and 36%.

5 CONCLUSIONS

In this paper, we have presented M-Show, an advanced WLAN based position estimation system in multi-floor buildings, and performance evaluation against analogous systems is also provided.

M-Show assimilates the efficient methods adopted in previous systems, made improvements to them and forms a novel position methodology. Furthermore, M-Show analyzes the new problems which rise in more demanding applications and developed strategies to handle them, which provides a precedent for the future research and systems.

M-Show presented a Fuzzy Empirical Signal Model that records empirical signals sampled in a variety of environment conditions, which gives more comprehensive and authentic description of radio signal distribution under different environmental conditions. Also, M-Show made improvements to the traditional ways of map clustering, by dividing the map into Intelligent Areas (iAreas), the size of which can change according to the granularity required. The idea enables a variable positioning granularity within the same map. In the position estimation phase, M-Show utilizes the regulation of propagation of an AP's signal, and developed a position pre-determining strategy called AP Close Range Threshold, which can easily discover users who are close to APs. M-Show also made advances in the Joint-Probability Calculation by the introducing of the parameter Not-Null-Scale, which makes the probability calculation more credible. Last but not least, M-Show developed a strategy called the Fluoroscopy to distinguish vertically overlapping positions of different floors.

We deployed the system of M-Show in Shanghai Science and Technology Museum, China. Experimental results show that M-Show achieves a high locating accuracy of 93% probability within 3 feet around the user's actual position with lower computation cost.

In the future, we plan to do in-depth study on the technology of data structure and compressed data storage to further reduce the size of our Fuzzy Empirical Signal Model. In addition, we will try increasing the granularity of iArea, and deforming iAreas to improve system adaptability, and analyze how the probability calculation process should be polished to meet more exquisite requirements of future applications.

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