Indoor Location Estimation Using Radio Beacons

Uzair Ahmad[*a], Young-Koo Lee[a], Sungyoug Lee[a], Chongkug Park[b]
[a]Department of Computer Engineering, [b]Department of Electronic and Radio Engineering,
Kyung Hee University, Korea

ABSTRACT

We present a simple location estimation method for developing radio beacon based location system in the indoor environments. It employs an online learning approach for making large scale location systems in a short time collaboratively. The salient features of our method are low memory requirements and simple computations which make it suitable for both distributed location-aware applications based on client-server model as well as privacy sensitive applications residing on stand alone devices.

Keywords: Real time Learning, Location Systems, Semantically Meaningful Locations

1. INTRODUCTION

Location systems form a fundamental component of envisioned ubiquitous computing applications. Several location based services are poised to enrich the way people interact with computers such as activity recognition, personnel management, asset tracking. Global coverage of GPS is considered as most potent example of a ubiquitous location system but it faces no availability of satellite signals in densely populated urban areas in general and especially in the indoor environments. Recently Wireless LAN (WiFi) based location systems have gained a significant attention from research community [2, 4, 6] as well industry [1, 3, 5]; mainly because pervasive availability of WiFi in urban areas and proliferation of wireless network enabled commodity handheld devices.

The WiFi based location systems can be coarsely characterized based upon two aspects; i) The granularity of location estimate and ii) The *prior* knowledge which the system needs to be known before learning. Coarse grained location systems, such as Intel's Place Lab[3], provide 20 to 50 meter accuracy and are more suitable for outdoor scenarios, whereas fine grained location systems, such as Ekahau [5], are befitting for indoor environments and achieve up to 3 meter accuracy. On the other hand, the division based on *prior* knowledge is present in both coarse grained and fine grained systems. Some systems require a detailed radio map of target area which provides the basis for developing a mapping function between physical space and signal space. Since creation of radio map is human intensive task, another class of systems avoids manual creation of radio map by using sophisticated radio wave propagation models. Nevertheless these models require detailed information about the position of WiFi access points, building structure, materials and obstacles; which, needless to mention, is often not easily accessible.

We present a novel approach to develop WiFi based location systems which do not require either a radio map or site specific propagation model while achieving medium scale accuracy. Salient features of this approach are

i) Real time learning of the relationship between signal space and physical space which results in lowering the entry barrier for the end users. Furthermore, the end users can define the specific area of interest which is suitable and meaningful to the semantic needs of location aware applications. We refer to this concept as 'Semantically Meaningful Location Context' (SML) in next sections.
ii) Privacy protection: A mobile device can compute its location in a completely passive manner which enables self-governed privacy protection.
iii) Unlike enterprise location systems, our approach delivers self-contained location estimation and does not even require network connectivity which is basic assumption in most of previous location systems. This capability achieves Personal Location System concept which functions independent of classical request-response interaction between clients and server.
iv) A collaborative development model can be realized which enriches the system by a growing community of users. It shall achieve the ease of development by empowering non-professional developers to build, extend and customize

[*] Contact Author Email: uzair@ieee.org

location systems using high level abstractions without knowing the underlying technology. Due to the limited space, we are not presenting the details of use cases and technicalities of how knowledge sharing occurs among collaborative users. This short paper only explains the learning mechanism of our method. Nevertheless, readers are encouraged to study the key prototype and important aspects of our collaborative model in [7].

2. REAL TIME LEARNING

The learning of SML has two objectives, i) ***minmax***: finding minimum number of access point beacons which are maximally detectable in maximum of target area ii) Perform this search in finite number of scanning operations in real time. For further explaining the dynamics of *minmax* learning the component notations are presented as follows. Let C represent a certain area and *minAP* is the minimum number of access points which maximally cover the C and machine needs to discover them in s_n number of scanning operations. The learning occurs by first considering all detectable access points as the candidates for uniquely identifying a semantically meaningful location. As new set of access points come, within the same semantically meaningful context, into the detection range of learning device the system selects/prunes out the access point which have lesser detection probability than others. This process goes on until *min*imum number of strongly identifying access points are searched out from a bunch of weakly identifying access points. This pruning function is governed by externally adjustable lower and upper detection probability bounds denoted as P_l, P_u respectively. Let $\{AP_i^{(h,nh,x,P)}\}$ denote a set of access point beacons where *i* indexes over each AP in the set, and superscripts {*h*,*nh*,*x*} represent four properties of each member access point. i) total number of times an AP is heard in s_n scans by the learning device, ii) total consecutive number of times an AP is not heard , iii) *x* stands for a Boolean flag which governs the self-regulatory mechanism to prune an unnecessary access point from the system iv) *P* the probability of an access point being detected across a certain SML. In the same row $\{cAP_i^{(h,nh,x,P)}\}$ represent the set of access points which are detected by the learning device, the $\{pAP_i^{(h,nh,x,P)}\}$ represents previously detected set of access points and $\{mAP_i^{(h,nh,x,P)}\}$ is the relative complement of $\{cAP_i^{(h,nh,x,P)}\}$ in $\{pAP_i^{(h,nh,x,P)}\}$. The $\{rAP_i^{(h,nh,x,P)}\}$ is used to denote the set of access points which system decides to remove from the $\{pAP_i^{(h,nh,x,P)}\}$ .The real time learning algorithm is presented in the following. Please notice that we use 'dot' notation to access any of the properties of an access point e.g. *AP*.*h*.

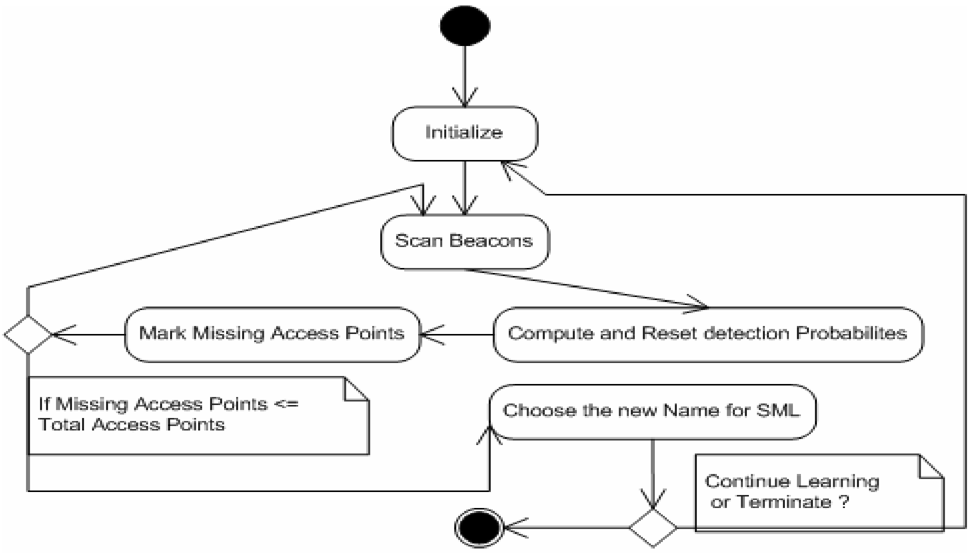

Fig 2: State Chart of the minmax Real Time learning Algorithm

2.1 The *minmax* Learning Algorithm

1. Initialize:
   a. s_n =1 , $P_l = .25$ detection probability lower bound, $P_l = .75$ detection probability upper bound, *minAP =3*
2. Scan Network: This operation creates fresh set of $\{cAP_i^{(h,nh,x,P)}\}$ and takes $\{pAP_i^{(h,nh,x,P)}\}$ as input parameter and returns $\{mAP_i^{(h,nh,x,P)}\}$ to the next step. In case device performs this operation for the first time then $\{pAP_i^{(h,nh,x,P)}\}$ is an empty set.
   a. For each *AP* in $\{cAP_i^{(h,nh,x,P)}\}$ its membership is checked in $\{pAP_i^{(h,nh,x,P)}\}$ such that
      i. If *AP* $\in \{pAP_i^{(h,nh,x,P)}\}$ then $AP.h++; AP.x = false$
      ii. Else $AP \cup \{pAP_i^{(h++,nh,x,P)}\}$
   b. For each *AP* in $\{pAP_i^{(h,nh,x,P)}\}$ its membership is checked in $\{cAP_i^{(h,nh,x,P)}\}$
      i. If *AP* $\{cAP_i^{(h,nh,x,P)}\}$ then $AP.nh++$
         1. $AP \cup \{mAP_i^{(h,nh,x,P)}\}$
         2. If *AP.nh > 5* then *AP.x =true*
   c. *Return* $\{mAP_i^{(h,nh,x)}\}$
3. Compute and reset detection Probabilities:
   a. For each *AP* in $\{cAP_i^{(h,nh,x,P)}\}$, $AP.P = \dfrac{AP.h}{S_n}$
4. Prune missing access points from the system
   a. For each *AP* in $\{mAP_i^{(h,nh,x,P)}\}$
      i. If $AP.P \le P_u \wedge AP.P \ge P_l$
      ii. $AP \cup \{rAP_i^{(h,nh,x,P)}\}$
   b. For each *AP* in $\{pAP_i^{(h,nh,x,P)}\}$
      i. If $AP \in \{mAP_i^{(h,nh,x,P)}\}$ then $\{pAP_i^{(h,nh,x,P)}\} = AP \setminus \{pAP_i^{(h,nh,x,P)}\}$
5. Choose the name of new Semantically meaningful location or Merge in previous context
   a. If $\{pAP_i^{(h,nh,x,P)}\}$.Count $\le$ *minAP* then Prompt user to input SML Name or Merge
   b. Else Go to Step 2.
6. Continue/Stop Learning

2.2 The Location Estimation Algorithm

Once SMLs and corresponding *distinguishing* access point beacons, denoted here as $\{contextBeacons\}$, are discovered by the *minmax* learning, the system estimates the location of a mobile device by means of a simple algorithm based on closest match between input beacon vector and the $\{contextBeacons\}$. The estimated context beacons are referred to as $\{predictionBeacons\}$. The pseudo code of this algorithm is presented below.

1. Initialize.
   a. Overlap = 0, maxOverlap = 0;
2. For each set of Access Points in $\{contextBeacons\}$
   a. If $\{inputBeacons\}$.Count >= $\{contextBeacons\}$.Count
      i. $overlap = \{contextBeacons\} \cap \{inputBeacons\}$
      ii. If *maxOverlap* < *Overlap* ➔ *maxOverlap = Overlap;* $\{predictionBeacons\}$ = $\{contextBeacons\}$
      iii. If *Overlap == 1* ➔ Break; *(A prefect match is found)
   b. Else
      i. $overlap = \{contextBeacons\} \cap \{inputBeacons\}$
      ii. If *maxOverlap* < *Overlap* ➔ *maxOverlap = Overlap;* $\{predictionBeacons\}$ = $\{contextBeacons\}$

3. EXPERIMENTAL SET UP

We conducted extensive experiments in a multi floor building to evaluate and characterize the performance of our approach. Results show a competitive accuracy, up to 10 meters, which is significantly better than other approaches which do not use radio map. On the other hand our approach does not require the prior knowledge about the positions of access points and environmental parameters.

Fig. 1. Map of the experimental site (Covered Aread Appx 2500 Square Meter).

Fig 1 shows the floor plan of the site building along with the location markers where we collected training and test beacon data as well as the position of WiFi access points. We used approximately 200 scanning operations to collect training beacon data while walking through the corridors of each floor. The empty circle marks on the Fig 1 map show the locations where we performed scanning operations. On the other hand the test data collection locations are marked as dot inside the circle. The real strength of our learning algorithm is tested by using the beacon data of densely occupied rooms.

There are total 16 WiFi access points used in our experiments. Table 1 shows the floor wise placement of each access point and corresponding SMLs. Last four digits of the MAC address is used to identify each access point as shown in last column of table 1. Due to severe multi path effects and dynamics of indoor academic environment, detect-ability of access points ranges from 2 to 16 depending upon the receiver location. Therefore discovering, in real time, the right number and combination of access points which can distinguish SMLs with high accuracy is main contribution of our method.

Table 1. Placement of WiFi Access Points in 5 floors of Engineering Building

Floor	Corridor	Semantically Meaningful Locations	Access Point MAC
1	1	Computational Physics Labs	8135
1	2	Photo-Electronics Labs	5139
1	3	Institute of Natural Sciences	5035
1	4	Natural Sciences Lecture Rooms	5883
2	1	Robotics Labs	9235
2	2	Biomedical Lecture Rooms	7199, 9207
2	3	Applied Biomedical Engineering	
2	4	Administration Offices	8203
3	1	Computer Engineering Labs	7195
3	2	Radio Engineering Labs	9239
3	3	Impedance Imaging Research Labs	2243
3	4	Faculty Offices	5823
4	1	Student Unions Offices	
4	2	Radio Engineering Lecture Rooms	5551
4	3	Bio-Medical Labs	
4	4	Lecture Rooms	5535, 5543
5	1	Laser Engineering Labs	5659
5	2	Communication Labs	6079
5	3	Astrophysics Labs	
5	4	Microware/Ultrasonic Engineering Labs	5559

4. RESULTS

Due to the space limitation we present results of only 3rd Floor of our experimental building site. This distance error is measured as absolute deviation of the estimate from actual location i.e. $e = \frac{\sum_{i=1}^{N} \left| l_i - l_i^{/} \right|}{N}$ where l_i is the actual location where i^{th} beacon vector was recoded and $l_i^{/}$ is the corresponding location estimate.

Table 2. Training and Test error of minmax Algorithm

	Training Vectors	Training Error e	Test Vectors	Test Error e
Corridor 1	40	0	190	0
Corridor 2	50	0.08	190	0.20
Corridor 3	50	0.28	133	0.20
Corridor 4	60	0.12	152	0.25

The training beacon data were collected as a result of short visit of all four corridors. Whereas the test beacon vectors were collected by visiting each room. Table 2 presents distance errors rendered by our method for each corridor.

5. CONCLUSIONS

We presented a radio beacon based location estimation system for indoor environments which provides several desirable features. i) It requires no prior knowledge about the position of transmitter, signal strength radio maps or offline training of sophisticated machine learning methods. ii) The online learning *minmax* algorithm performs location to signal mapping in real time while the use is walking iii) A small portion of target locations are needed to be physically visited for successfully estimating, with high accuracy, the location of a device at a location which was unknown at training time. iv) Memory and computational requirement of our learning and estimation algorithm are lightweight enough to easily function on resource constricted devices and sensor nodes. Unlike other beacon based systems, such as PlaceLab and NearMe, our system enables users to define semantically meaningful locations.

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