The Election Algorithm for Semantically Meaningful Location-awareness

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ABSTRACT

The technology of multimedia content adaptation based upon the location of a target device can become the long expected killer application of ubiquitous computing. Easy to develop, lightweight, and robust location estimation is the core component of this technology. Until now, location estimation technology remains restricted to highly sophisticated hardware and networking infrastructure where semantics of the location information are defined and controlled by service providers. We aim to lower the technical and infrastructure barriers to allow general users to define and develop the semantically meaningful location systems. This paper presents a simple location estimation method to build radio beacon based location systems in the indoor environments. It employs an realtime learning approach which requires zero prior knowledge. The salient features of our method are low memory requirements and simple computations which make it desirable for location-aware multimedia systems functioning in distributed client-server settings as well as privacy sensitive applications residing on stand alone devices.

Categories and Subject Descriptors

C.2.8 [**Mobile Computing**]: Algorithms Design; J.9 [**Mobile Applications**]: Location Sensitive; I.2.6 [**Machine Learning**]: Environment Perception and Modeling

1. INTRODUCTION

Location systems form a fundamental component of mobile and ubiquitous computing applications. Location awareness can enable several multimedia applications in ubiquitous computing environments. Location based content adaptation of such application is the key to realize hand held devices functioning as multimedia tour guides, escorts, adaptive computer interfaces and games. Despite a growing demand for easy entry into location awareness, the location estimation technology largely remains a proprietary asset. At the same time, the commodity devices such as PDA and cell phones are becoming the mobile multimedia platforms. Location awareness of these devices in indoor environments and urban areas is the key to realize above mentioned location based multimedia applications. Recently Wireless LAN (WiFi) based location systems have gained a significant attention from research community [1],[3],[8] as well as industry [5], [6],[12]; mainly because of the pervasive availability of WiFi in densely populated urban/indoor environments and proliferation of wireless network enabled commodity devices.

We present a novel method to develop WiFi radio beacon based location systems which, unlike previous systems, present no entry barrier to the end users/developers. It does not require either a radio map or site specific propagation model while achieving medium scale accuracy in application specific areas defined by end user. The salient features of our method 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 Area' (SMA) in rest of the paper. ii) Privacy protection: A mobile device can compute its location in a completely passive manner which enables self-governed privacy protection. iii) Unlike enterprize 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 enables Personal Location Systems which function independent of classical request-response interaction between clients and server.

A comparative overview of existing research is presented in section 2. A brief introduction to the terminology and notations is provided in section 3. The election algorithm dynamics and its learning properties are discussed in section

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4. Section 5 presents a field study in real environment and performance of Election algorithm in terms of learning and recognition of semantically meaningful areas. We identify further improvements and shortcomings in current version of Election algorithm in section **??** as future direction of this work.

2. RELATED WORK

The concept of using radio beacons, particularly WiFi, for locating the mobile devices is not new. For the sake of easy understanding we coarsely categorize WiFi signal based location systems 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[6], provide 20 to 50 meter accuracy and are more suitable for outdoor scenarios. The NearMe [5] is another example of such systems. The fine resolution location systems, such as RADAR [1], Ekahau [12] and some others [4], [8] 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.

This work falls in coarse resolution systems category but the idea of interactive real time learning is also realized by high resolution systems such as Nibble [2] and Locationware [10]. As a secondary benefit, our method can help enhance accuracy of fine resolution system by providing partitions in feature space for modular classification model proposed in [8] and [9].

The RightSpot[3] is an outdoor location system which utilizes FM radio beacons instead of WiFi. This technology localize devices based on ranking of signal strengths of different FM beacons. Thus for n FM radio stations, $n!$ rankings can be observed each at presumably different location. The system encodes each permutation into a unique hash code. An off line learning phase is conducted to construct normalized histograms to estimate the probability of each beacon that appears at certain location. After system builds these histograms for all target locations, the system computes posterior probabilities using naive baye's rule and assign the most probable location to be the current location of the reporting device. Our problem is to employ beacon signals in the indoor settings and, unlike RightSpot, the election algorithm does not require prior knowledge of available beacons in the target field. This means that the device knows nothing before it starts learning. Moreover, it aims at learning of custom boundaries in physical space in real time when no prior knowledge of signal visibility is available.

The aim of the NearMe[5] system is not to locate a device but to discover other objects in the proximity of a client device. It works on a client server communication model and achieves proximity object discovery by employing a mechanism of template matching of detected radio beacons. Attractive feature of NearMe is that it requires neither prior knowledge and nor any off line training to work. The election algorithm shares 'zero prior knowledge' and template matching aspect with the NearMe system. However, the scope of the election algorithm is not just discovering proximity objects. It enables several other location aware applications in addition to just discovering the neighboring devices. Nevertheless, it can achieve the same capability in specific areas defined by user in the location space. This means that it can discover neighboring objects in custom created boundaries which are suited to particular applications.

The PlaceLab[6] is another beacon based localization system which allows mobile devices to locate themselves in a completely passive manner. However, unlike NearMe, it requires prior knowledge of approximate location of radio beacons in order to locate devices. The position and identification of all radio beacons is stored in a database. When a device needs to locate itself, the PlaceLab searches the database for the beacon whose signal strength is reported strongest among all and then that location of that beacon is supposed to be the approximate location of the device. This database search mechanism is particularly suitable for outdoor environments, as noticed by the authors [6], and it is not suitable for the indoor environments where dense WiFi deployments where strongest signal strength criteria can produce misleading estimates. The election algorithm particularly targets indoor environments and no prior knowledge is required.

In our initial study [11] it was demonstrated that a beacon based localization system can provide better accuracy while preserving the three properties 1. real-time learning 2. Zero prior knowledge 3. End user Interactive development model, as mentioned in last section. This paper reports a succinct description of the election algorithm to formally model the learning properties of our beacon based learning system by constructing an analogy to the concept of well known political elections. The resulting system provides robust learning dynamics and better recognition results.

3. TERMINOLOGY

3.1 The Signal Space

Here we present essential terminology to facilitate further discussion on beacon based localization problem. The core problem of inferring location information from radio beacons is to find functional dependency between signal space and physical space. We refer to the basic relationship between a radio beacon and area as Signal Coverage Area SCA which is a collection of locations where signal from a particular beacon can be detected. This means that a receiver device can infer its location whenever it receives signal from a particular beacon. However, in denser deployment scenarios such as indoor environments, more often signal from multiple beacons is undetectable at most of the locations. Which can help divide an SCA into two categories. i) the single beacon Distinguishable Signal Coverage Area $DSCA$ is the subset of SCA where the signal strength from beacon b is strongest among signals received from all beacons. ii) the general Distinguishable Signal Coverage Area (gDSCA) is the SCA created by more than one/one beacon. Figure 1(b) shows a pictorial representation of SCA and $DSCA$.

3.2 The Location Space

The sense of location that we target to achieve to enrich

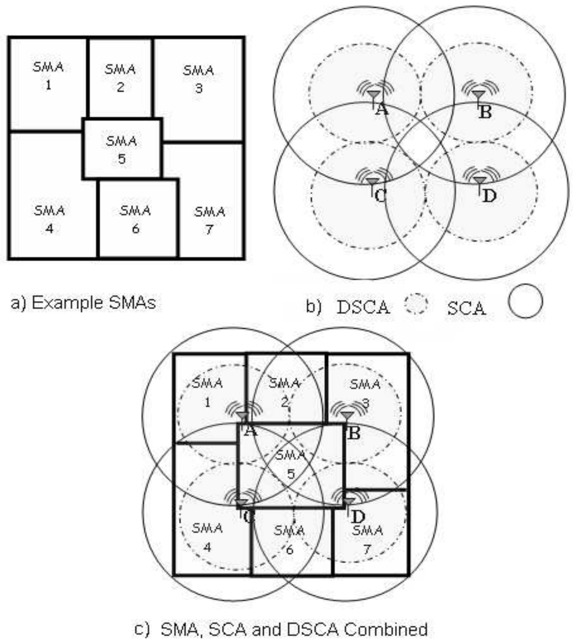

Figure 1: Example of $SCA, DSCA$ and $gDSCA$

computing services in indoor environments is completely defined by the semantic needs of target application. We refer to the boundary of this location sense as Semantically Meaningful Area (SMA) which is a collection of contagious locations that a location enhanced service perceives as an area of interest. This means that when a roaming user enters, or leaves, a particular SMA, the system invokes location sensitive applications and services to seamlessly adapt and alter user's environment. Figure 1(a) shows an example field where five SMA are defined by the target applications. Now considering the location based applications perspective, it is very unlikely that location sense of an application can be improvised solely by the physical boundaries defined by coverage area of a beacon. In straight forward cases, if an SMA matches SCA then location could be determined based on a single beacon signal. In overlapping coverage if some SMA matches a $DSCA$ then localization problem becomes a case of finding a beacon with the strongest signal strength and associating device's position the location of that beacon. Nevertheless, in practical problems, occurrence of above situation is very rare because of possibly complex and arbitrary geometry of an SMA. Particularly in indoor environments, multi-path propagation can cause complex overlaps and entangled $DSCA$s which do not match with the SMA. A similar situation is depicted in figure 1 (c), especially in SMA five.

3.3 The SMART Code

We strive to overcome the limitation of conventional beacon based localization in complex indoor environments. It is hypothesized that multiple beacons are needed who might form one or more $gDSCA$s to constitute an arbitrary boundary of an SMA. We devise a system for interactive, online learning of $gDSCA$s with zero prior knowledge. It discovers stable and reliable $gDSCA$s from a the signal space and, by means of human-computer interaction, stores semantic meaning of the location in $SMART$(SMA Recognition Templates). $SMART$ is a smallest set of beacons whose members can accurately identify a given SMA. It couples location space and signal space such that these coupling can be used as reference for localizing mobile devices.

4. THE ELECTION ALGORITHM

Election algorithm provides a novel learning machine which can discover n best representatives out of m contestants. It has autonomous mechanisms to i) cater for the noisy nature of indoor radio wave propagation and ii) prune the non-representatives out of the system such that only winners survive. The learning conditions of this algorithm make it distinguishable from the conventional voting based localization algorithms i) Learning should happen online while the device is moving around in the problem space ii) Prior knowledge of the position of beacons is not available.

4.1 A Motivational Analogy

The intuition behind this algorithm is created by making it analogous to an election process where multiple candidates contest to hold representative offices of a constituency. The polling results produce a ranking which reflects the degree of representativeness of each candidate such that highest office is awarded to the candidate who wins maximum votes from a sample population in that constituency, then the next office is given to the next highest winner and so on. The notion of more, less or no representativeness of a beacon is due to the fact that a beacon may be detected over a physical space, an SMA, more consistently than others and vice versa. The more consistent detection of a beacon implies that it can better represent an SMA than the less consistently detected beacon. In this manner, the individual beacons contest with each other in order to win a representative office in a constituency or SMA.

The polling process of Election algorithm differs from well known method in terms of voting time and compilation of results. In the ordinary elections polling takes place simultaneously at different locations of a constituency at given time and results are compiled afterwards. This polling method is applicable because all the contestants know their constituencies. However, consider a situation in which candidates do not know their constituencies but an election must be held. In the same sense, our aim is to discover appropriate beacon representatives for semantically meaningful areas while no beacon knows its own position. Owing to the special nature of the learning problem Election algorithm conduct polling sequentially and results are compiled as the voting continues.

The learning activates as soon as device starts reporting the detected beacons to Election algorithm and continues until all possible $gDSCAs$ are discovered and assigned to appropriate $SMAs$ or the location system developer externally stops it. Results are compiled while the device moves around in the area of interest on an arbitrary path reporting detected beacons. Election algorithm tracks the detection of individual beacons and construct a temporary rankings of beacons based upon their detection consistency. The system prompts the developer for naming the newly identified $gDSCA$ as soon as the device moves in an area which is not represented by the SMART members. Finalization of this interaction results in creation of a SMART.

4.2 Notations Involved

A brief description of notations is required before we explain the learning dynamics of Election algorithm. It concerns objectification of two concepts i) a radio beacon and ii) a set of beacons. Every object possesses some properties and provides interfaces to access those properties. We use $A_{[b]}$ notation to represent each group where A is the group name and b indexes over group members. Each group provides interfaces to perform some basic operations onto the group. These interfaces are mentioned using "." after the concerned object such as; $A.Count$ gives total members of the group, $A.Contains(beacon)$ answers group membership enquiry and $A.Add/A.Remove$ allows adding/removing beacons to/from a group.

An individual beacon is represented as $B_{(d,nd,dP,x)}$ possessing four properties. Algorithmic description uses boldface to show value of any of these properties e.g. $B_{(\mathbf{d},nd,dP,x)}$ gives value of d. The d holds total number of times the beacon is detected since learning started, nd is number of times a beacon was not detected, dP is the detection persistence and x is a boolean flag which indicates the system to remove a beacon from the candidates set.

Listing 1 shows different sets of beacons as well as related representations of computations which we will explain while discussing the learning dynamics.

Listing 1 Notations concerning Algorithm [2]

Parameters
$m\tau$: Missing Beacon Tolerance
τ: Limit on Size of a SMART
Define Global
$C_{[c]}$: Collection of beacons appear in latest scan
$L_{[l]}$: Collection of beacons appeared in last scan
$M_{[j]}$: Collection of missing beacons
$T_{[k]}$: Collection of beacons trail
$ChangeDetected$: A boolean flag
S_c: Scan count
m: Consistently missing beacons

4.3 The Learning Dynamics

The Election algorithm forms conceptual groupings of beacons and continuously performs simple set operations on these groups in order to finally discover the $gDSCA$. Membership of these groups is bound to change as the moving device keeps on scanning the beacons from place to place. Algorithm 2 provides an abstract description of operational flow which is composed of three main steps.

4.3.1 Scanning Beacons

In the first step, at an arbitrary location a the network is scanned to detect the beacons who claim to be the representatives of that location. Upon each scanning operation, or polling call, all detected beacons are grouped as latest scan set, $C_{[c]}$, and the previously scanned beacons are assigned to another group denoted as $L_{[l]}$. Objective of this grouping is twofold; i) Detecting change in signal or location space ii) Tracking detection/absence of an individual beacon. Detecting change in location or signal space is important from system development point of view. Considering the election analogy, for the sake of fairness, it is necessary that at each location one beacon casts only one vote. Which requires that equal number of scanning operations should be performed at all locations. However, it is very unlikely that the human carrier of learning device will keep a consistent speed. The computations can get biased towards detected beacons in case carrier stays at a location longer than the other. However, if scanning/voting results are similar at two adjacent locations then it would not affect the final results. Based upon this intricacy, we repose the issue of fairness by changing the equal vote counting condition to only dissimilar vote counting. It means that system learns only when there is a change in signal space. This change is important even if carrier is stationary or mobile at scanning time. It eliminates the consistent speed constraint from system developer as well as redundant operations. On the other side, Even though location is changed but there is no change in signal space then no learning shall take place. Machine perceives changed signal space in three cases when; i) a new beacon appears in $C_{[c]}$ ii) a beacon is missing in $C_{[c]}$ which was detected in $L_{[l]}$ iii) both (i) and (ii). The record of respective detected and absent beacons are updated once change in signal space is found. The system maintains two other groupings as well; 'beacon trace' $T_{[k]}$ and missing beacons $M_{[j]}$. The $T_{[k]}$ is the superset which contains all beacons which get detected since learning started. While $M_{[j]}$ are all the beacons which appeared at some point but vanished later. Besides updating detection/absence record, system adds newly detected beacon of case (i) to the T and missing beacons of case (ii) to M. Clearly, no change in $T_{[k]}$ and $M_{[j]}$ occurs if the signal space remains unchanged.

$$T_{[k]} \cup C_{[c]} \setminus T_{[k]} \Rightarrow \{c : c \in C_{[c]} andc \ni T_{[k]}\} \tag{1}$$

$$M_{[j]} \cup T_{[k]} \setminus C_{[c]} \Rightarrow \{k : k \in T_{[k]} andk \ni C_{[c]}\} \tag{2}$$

Algorithm 2 The Election Algorithm

Define Variables (Listing 1)
Scan Beacons and Track Detections
  {see procedure 3}
while $ChangeDetected$ is 1 **do**
  Determine detection/absence persistence
  {see procedure 4}
  if $m > 0$ **then**
    Remove insignificant beacons From T
    {see procedure 5}
    if $T.Count \leq \tau$ **then**
      SMART $\leftarrow T$
    end if
  end if
end while

4.3.2 Detection/Absence Persistence

In case of change in signal space, the learning continues to the second step. The distinguishing nature of our election method is to compile the results while voting is taking place in a continuum. This requires watching the candidates who are always or mostly detected. This information is captured as detection persistence dP of each individual beacon since the first scan (voting) took place. The dP is a measured as the ratio of detection count and total number of scans (or

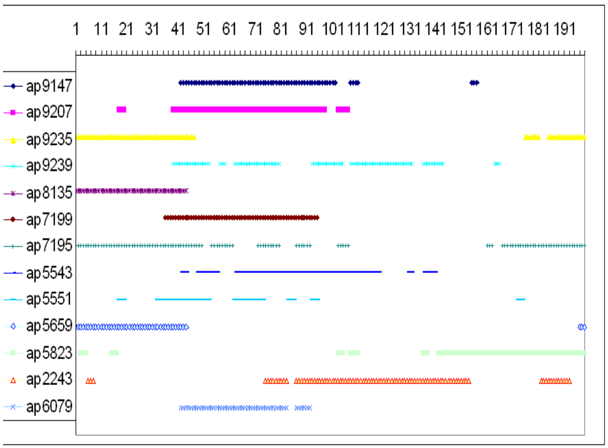

Figure 2: Beacons in target field

Procedure 3 Scan Beacons and Track Detections

if $L_{[l]}$ is $C_{[c]}$ **then**
  $ChangeDetected \leftarrow 0$
  $Stop$
else
  $ChangeDetected \leftarrow 1$
end if
for c^{th} beacon b in $C_{[c]}$ **do**
  $b_{(\mathbf{d++},nd,dP,x)}$
  if $\neg T.Contains(b)$ **then**
    $T.Add(b)$
  end if
end for
for k^{th} beacon b in $T_{[k]}$ **do**
  if $\neg C.Contains(b)$ **then**
    $b_{(d,\mathbf{nd++},dP,x)}$
    $M.Add(b)$
  end if
end for

voting calls).

$$dP = \frac{Detectioncount}{Totalnumberofscans} \tag{3}$$

The system computes dP for each beacon who is member of $T_{[k]}$ and detection count S_c denominator is incremented for next round of voting. Notice that if the detection of change in signal space has subtle impact on dP as well. If device stays at a location for extended period then temporal absence of a beacon at that location can cause unfair drop in dP which results in weakening its candidacy for becoming the representative. The temporal absence of beacons is commonplace phenomenon especially in indoor environments. It can be observed in figure 2, which shows a snapshot of the real data about detection of beacons in one of our target fields. This happening can also cause abrupt removal of a beacon from candidates set and When a beacon appears again after short absence all its previous reputation, in terms of dp, is lost. A cushion is provided to overcome this potentially perturbing situation. The $m\tau$ is an externally specifiable parameter which allows the system to tolerate temporarily missing beacons. Due to this mechanism an absent beacon remains in beacon trace superset $T_{[k]}$ until it is consistently not detected more than $m\tau$ times. Even though it slowly degrades beacon reputation but prohibits abrupt removal of a legitimate beacon. Once a beacon is not detected even for extended time, system marks it as removable from the beacon trace as a natural consequence. Besides marking, all such beacons increment the removable beacon count m so that further procedures can take place.

Procedure 4 Computing Detection/Absense Persistence

$m = 0$
if $changeDetected$ **then**
  for k^{th} beacon b in $T_{[k]}$ **do**
    $b_{(d,nd,\mathbf{dP},x)} \leftarrow b_{(\mathbf{d},nd,dP,x)}/S_c$
  end for
  $S_c \leftarrow S_c + 1$
  for j^{th} beacon b in $M_{[j]}$ **do**
    if $b_{(d,\mathbf{nd},dP,x)} > m\tau$ **then**
      $b_{(d,nd,dP,\mathbf{x})} \leftarrow 1$
      $m = m + 1$
    end if
  end for
end if

4.3.3 *Removal consolidation*

The final goal of first two steps was to segregate the overlapping beacons in two sets; i) The beacon trace $T_{[k]}$ which gives a ranking of all contestants according to their reputation measured as dP and ii) The missing beacons set $M_{[j]}$ which is a set of beacons who could not qualify as legitimate candidates. When one or more beacons are perceived as missing by the system, the removal consolidation ensues for a possible SMART formation in third step. At this stage Election algorithm enacts four further sub groupings of beacons trace based upon there detection (as well as absence) persistence reputation; SMART, 'To be removed' $R_{[i]}$, Immature beacons $iM[i]$, Weak beacons $wK_{[i]}$ and Missing beacons. The dP divides missing beacons into two subgroups; i) 'To be removed' and ii) Conclusive. Each of them have opposite role to play. Distribution of these groups with respect to dP is shown in figure 3.

4.3.4 *Cautious creation*

The 'to be removed' missing beacon set initiates the removal process so that the representative offices should be assigned to legitimate SMART. However, system takes a cautious approach to avoid redundant creation of $gDSCA$ where largely similar SMART represent nearby locations. As a by product, this approach gives another chance for make up to the temporarily absent beacons. This approach delays SMART creation until members of all other groups are less than SMART size τ.

$$(iM.Count + wK.Count + R.count) \leq \tau \tag{4}$$

4.3.5 *Immediate creation*

System can encounter a situation which calls for urgent creation of SMART. It occurs when the members of 'conclusive set' who won majority votes ($dP > .7$) but are not available for this location onwards anymore. Therefore it immediately eventuates the creation of a reliable $gDSCA$.

The discovery of $gDSCA$s is governed by two parameters i) $m\tau$ missing beacon tolerance and ii)τ SMART Size limit.

Procedure 5 Removal Consolidation and SMART Formation

Local Definitions
$R_{[i]}$: Collection of 'to be removed' beacons
$iM_{[i]}$: Collection of immature beacons
$wK_{[i]}$: Collection of weak beacons
iC: Insignificant beacons count
if $m > 0$ **then**
  for j^{th} beacon b in $M_{[j]}$ **do**
    if $b_{(d,nd,dP,\mathbf{x})}$ is 1 **then**
      $R.Add(b)$
    end if
  end for
  for k^{th} beacon b in $T_{[k]}$ **do**
    if $b_{(d,nd,\mathbf{dP},x)} < .40 \wedge b_{(d,nd,dP,\mathbf{x})}$ is 1 **then**
      iM.Add(b)
      $iC = iC + 1$
    else if $b_{(d,nd,\mathbf{dP},x)} < .70 \wedge b_{(d,nd,\mathbf{dP},x)} > .40 \wedge b_{(d,nd,dP,\mathbf{x}}$ is 1) **then**
      wK.Add(b)
      $iC = iC + 1$
    end if
  end for
  if $(T.Count - iC) \leq \tau$ **then**
    for i^{th} beacon b in $R_{[i]}$ **do**
      T.Remove(b)
    end for
    if $(T.Count > \tau$ **then**
      if $(T.Count - iM.Count) \geq \tau$ **then**
        for i^{th} beacon b in $iM_{[i]}$ **do**
          T.Remove(b)
        end for
      else
        Remove only $\tau - (T.Count - iM.Count)$
      end if
      if $(T.Count - wK.Count) \geq \tau$ **then**
        for i^{th} beacon b in $wK_{[i]}$ **do**
          T.Remove(b)
        end for
      else
        Remove only $\tau - (T.Count - wK.Count)$
      end if
    end if
    Form new SMART with the T
  else
    Continue
  end if
end if

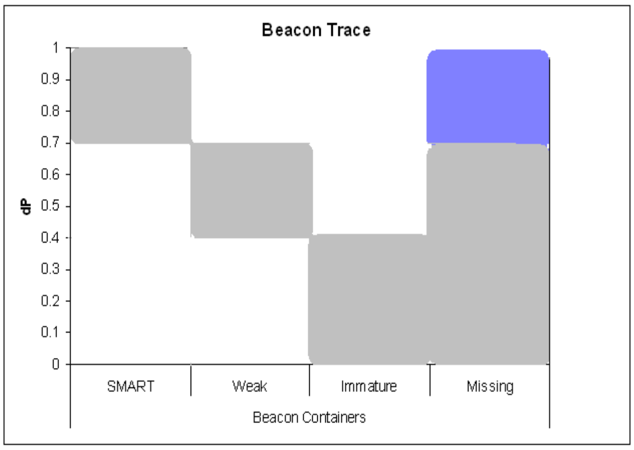

Figure 3: Beacon Containers: Sub sets of beacon trace

4.4 The Recognition Part

The influence of election analogy does not end at formation of $SMART$s. It works after finding the suitable representatives too, when a device needs to be located. At that time the detected signals are put forward to the representatives of all constituencies ($SMAs$) for checking the possible membership of device to an SMA. The final decision is again made based upon maximum votes won using the conventional polling strategy. Algorithm 6 shows the sequence of operations for recognizing the location of a mobile device. In the next section we present evaluation results of a field test study that we conducted.

Algorithm 6 Election Algorithm- Recognition Part

$SMARTc = CollectionofSMARTs$
$pSMART = PredictionSMART$
$dBeacons : Detectedbeaconsvector$
$maxOverlap : Thedegreeofsimilarity$
for i^{th} $SMART$ s in $SMARTc$ **do**
  $Overlap = s \cap dBeacons$
  if $maxOverlap < Overlap$ **then**
    $maxOverlap \leftarrow Overlap$
    $pSMART = s$
  end if
end for

5. FIELD TEST RESULTS EVALUATION

We evaluated the Election algorithm performance in a real indoor environment. The signal coverage of WiFi beacons varies from place to place between as low as 2 to as high as 16 beacons. Figure 4 shows the geometry of the building along with the points where we took training and test data. For the sake of clarity here we present only one scheme where 4 Semantically Meaningful Areas were defined as our areas or interest. Each corridor shown in figure 4 represents an SMA.

Results show that $gDSCA$ formation depends on the missing beacon tolerance and $SMART$ size. In order to characterize the variance of performance, here we present $gDSCA$ formation results with variety of these two parameters. Fig-

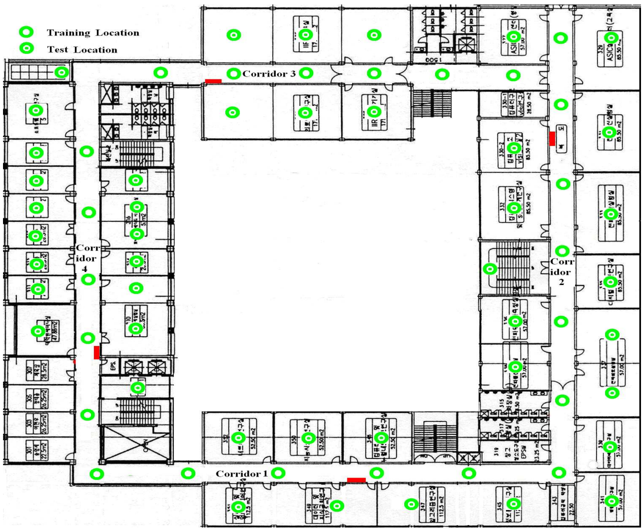

Figure 4: Field Map and testing Environment

ure 5 bar graphs show number of $gDSCA$ changes with respect to $m\tau$ and τ. It is interesting to note that increasing the tolerance parameter results in lesser number of $gDSCA$ discoveries. From system development stand point zero tolerance can identify numerous $gDSCA$s in signal space but machine requires lot of human attention at the same time. Moreover, lesser $m\tau$ values increase the risk of redundant $SMART$s being created. The redundancy not only increases the memory and computational requirements, it adversely affect the recognition ability of the algorithm.

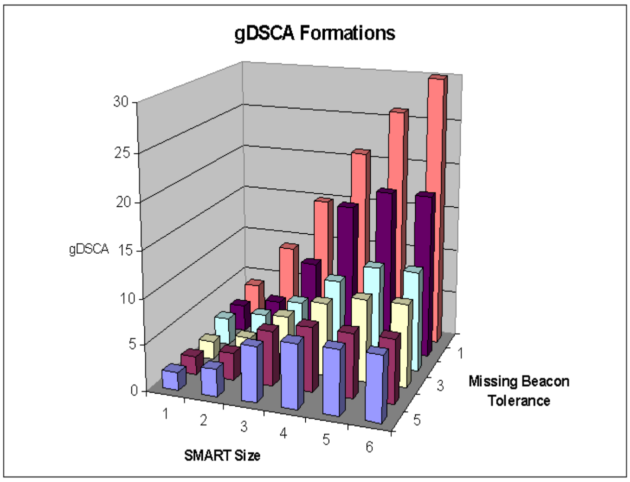

Figure 5: $gDSCA$ Formations

The recognition rate of Election algorithm is shown in figure 5 bar graphs for different values of $m\tau$ and τ. The SMA recognition error is measured as ratio of incorrect assignments to the total number of training or test vectors. The recognition error generally reduces for middle order options of $m\tau$ and τ. Nevertheless for the extreme values the error aggravates. Especially for $\tau = 1$ where only one beacon is used to estimate the location, like in PlaceLab, the recognition rate remains worse for all values of $m\tau$. This shows the inadequacy of one beacon based location estimation in the indoor environments. On the other hand, increasing the missing beacon thresh hold, $m\tau$ reduces overall error. This explains that $m\tau$ plays an important role in selecting better representative beacons. However higher values of $m\tau$ obliterate most of the $gDSCA$ as can be seen in the fig 5.

6. CONCLUSIONS AND FUTURE DIRECTIONS

An online, incremental and interactive learning algorithm is presented to develop radio beacon based location estimation system for indoor environments. Several location sensitive multimedia content adaptation applications require location estimation as key capability. The Election algorithm provides several desirable features which are not available in the current state of the art. Firstly, it requires no prior knowledge about the position of transmitter, signal strength radio maps or off line training of sophisticated machine learning methods. Secondly, the location to signal mapping is performed in real time while the device is moving around in the vicinity. Thirdly, a small portion of target locations are needed to be physically visited for successfully estimating the location of a device at a location which was unknown at training time. Finally, the resulting methodology enables users to define semantically meaningful locations according the the needs of target applications.

The Election algorithm learning and recognition properties face certain limitations. As mentioned in section 4.3.1, there are three cases when change in location or signal space is perceived by the learning machine. All of these three cases are based upon mere detection of a signal. However, signal strength can provide more sensitive change detection method which is not considered in this version of the algorithm. For example, consider an SMA which is defined by two radio beacons. When a mobile device walks through this SMA, it will not detect any change in signal/location space even though device is moving. How ever, if signal strength of each beacon is monitored then there shall be two sub areas defined by relative signal strength of two beacons. Signal strength based change detection can increase the sampling rate reflecting in more refined detection persistence (equation 3). The current state of election algorithm does not consider a scenario when the learning device visits certain areas more than one time. This limitation imposes single visit per location restriction of the developer. This restriction reduces the robustness and freedom of the end user to move around while device is learning. Current template matching mechanism is based upon naive vote counting. A more intelligent weighted vote counting can be improvised by incorporating signal strength and detection persistence of each member of a SMART. In future, we will enhance the Election algorithm to overcome these shortcomings.

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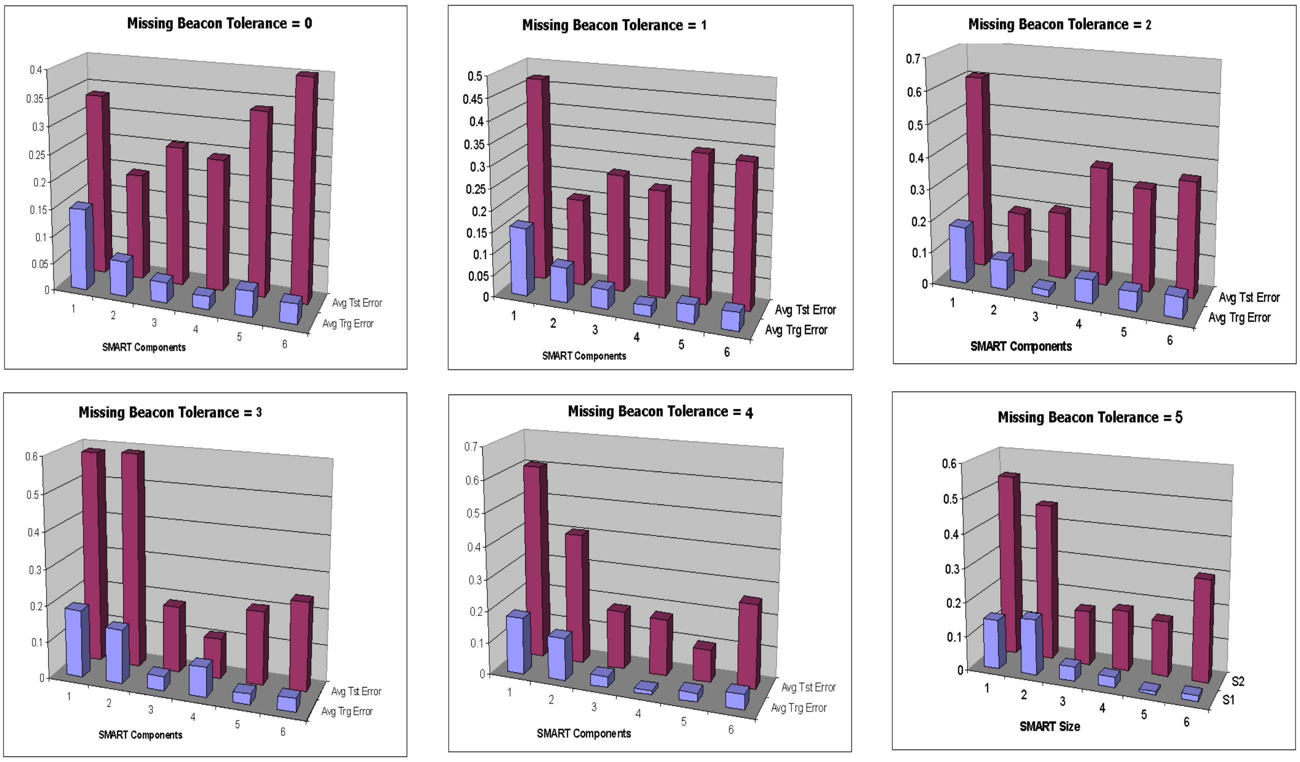

Figure 6: Aggregated over all SMAs Results: Affect of variations in Missing Beacon Tolerance $m\tau$ and $SMART$ size τ (x-axis) on SMA Recognition-rate (y-axis) of $SMART$. The z-axis show aggregated error for both training and test beacon vectors.

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