

Optimizing distribution of location sensors in location system

Haifeng Yuan, Qiang Ni, Wenbing Yao, and Yong-Hua Song

School of Engineering and Design, Brunel University, London, UK

Email:{eepghfy, qiang.ni, wenbing.yao, y.h.song}@brunel.ac.uk

Abstract: The proliferation of Wireless Local Area Networks (WLAN) has fostered a growing interest in the location-based services for WLAN users. For indoor WLAN systems, signal dispersion is highly disturbed. Therefore, how to improve the accuracy of the location sensing is a very challenging problem. Deploying location sensors as reference tags in the system is a viable and cost-effective method to achieve high location accuracy and has been verified in many cases. Till now, few research work has studied the impact of distribution of location sensors on the location accuracy. Here, we propose a novel algorithm to optimize the distribution of location sensors. Experimental results show that our proposed optimal scheme can significantly improve the location accuracy. This algorithm can be easily migrated to other cellular location systems.

1 Introduction

Wireless Local Area Networks (WLANs) are more and more commonly used in indoor environments. This fosters that location-aware applications have attracted increasing interest. Previous works addressed this problem in different ways. Traditional methods are based on propagation techniques. Although some efforts have been made, the positioning accuracy is still not satisfying till now. The fingerprinting technique is another method which based on the fact that received signals at different locations possess different electromagnetic characteristics. This can achieve fairly high positioning accuracy, but the on-site measurements can be a costly process and sometime is impossible.

By utilizing the concept of the reference tag into the system, one new location sensing technology is emerging recently [1,2,3,4] and has been verified as a viable cost-effective means. These tags serve as the reference points in the location sensing area and transmit their identification (ID) data to the network side with the network control. In the network side, system has a group of antenna, which can generate a signal strength vector for each tag as well as the objected MS. Since each reference tag's location coordinate is known, the AP will compute the distance by comparing the signal strength vectors received from the tracking tags and those from different reference tags'. Then using some of the nearest reference tags' coordinates to calculate the approximate coordinate of the objected MS.

It is obviously that how to deploy the reference tags in the service area is an important factor to the location accuracy. Till now few research studied on this issue, almost all the system are evenly deploy the tags in the system. In this paper, we analyzed the location accuracy effect by the tag distribution in the case that these group antennas mounted in one AP [4]. By using the high precision radio components, it is feasible to realize the signal difference between these closed distance antennas [5,6]. By theoretical analysis we get the optimized deploying scheme. Analytical results, verified by computer simulations, shows our scheme can significantly increase the location accuracy comparing to the evenly distributed methods. This scheme can also be used in some other cellars system outdoor environment. The analysis method can also be referenced for network planning and optimization.

2 System Model

Reference tag based location system use the Euclidean distance positioning algorithm to estimate the MS's location. That is: $E_l = \sqrt{\sum_{i=1}^n (g_i^l - h_i)^2}$, where g_i^l and h_i denotes the path loss from the antenna i to the location sensor l and the target MS, respectively. The target MS's position X can be calculated from the coordinates of the k nearest location sensors around the target MS, by using $X = (\hat{x}, \hat{y}) = \sum_{i=1}^k W_i (x_i, y_i)$, where W_i is the weight to the i^{th} location sensor in the neighbourhood of the target MS, and $W_i = \frac{\frac{1}{E_i^2}}{\sum_{i=1}^k \frac{1}{E_i^2}}$.

Fig. 1 shows a location sensing deployment example. The Access Point (AP), usually installed in the ceiling of central area, provides wireless data service for all Mobile Stations (MS) located in its covered area. The AP equipped three antennas units O_1, O_2, O_3 , which are placed on a circle and 120 angle

degree from each other. Suppose $d_{i,l}$, and d_i is the distance from the antenna i to the location sensor l and to the target MS, respectively. $g_i^l(\lambda)$ is the function that path loss from antenna i ($1 \leq i \leq 3$) by the distance to the antenna i , written as λ .

Considered that for any location sensor l , there is $d_{i,l} \gg \|O_i O_j\|$, where $j \neq i$. So, for any i , $g_i^l(\lambda) \doteq g^l(\lambda)$, here $g^l(\lambda)$ is the path loss function from the geometrical center of the three antennas to the location sensor l . So, We use $g^l(\lambda)$ as the approximation function for the $g_i^l(\lambda)$. Similar, $h_i(\lambda)$ is the path loss function by the distance for the target MS and it has the similar manner in this way. So, $h(\lambda)$ is used to approximated $h_i(\lambda)$.

To achieve the optimized distributed algorithm, we first, analysis the evaluate path loss for a random point (x, y) . Since for any location sensor l , $d_{i,l} \gg \|O_i O_j\|$, where $j \neq i$, is still exist. So, We use $g^l(\lambda)$ and $h(\lambda)$ as the approximation function for the $g_i^l(\lambda)$, $h_i(\lambda)$ respectively. Rewrite Euclidean distance positioning algorithm function, we can get the express for $h(\lambda)$ as the function shown as $h(\lambda) =$

$F \left[(x_1, y_1), (x_2, y_2) \cdots, (x_k, y_k), g_{(\lambda_1)}^l, g_{(\lambda_2)}^l \cdots, g_{(\lambda_k)}^l \right]$, where $\lambda, \lambda_1, \lambda_2, \cdots, \lambda_k$ are the distance from the AP to the random point (x, y) , and k neighbor location sensors $(x_1, y_1), (x_2, y_2), \cdots, (x_k, y_k)$, respectively. According to the principle of the Euclidean distance positioning algorithm, to obtain the

minimum $\sum_{i=1}^j \Delta p_i$ can be equivalent to:

$$\begin{aligned} \min \quad & \int_0^{2\pi} \int_0^{\lambda_{max}} [h(\lambda, \theta) - g(\lambda, \theta)]^2 d\lambda d\theta; \\ \text{s.t.} \quad & h(\lambda, \theta) = F \left[(x_1, y_1), (x_2, y_2) \cdots, (x_k, y_k), g_{(\lambda_1)}^l, g_{(\lambda_2)}^l \cdots, g_{(\lambda_k)}^l \right] \\ & (x_i, y_i) \in A, \quad i = 1, 2, \cdots, k \end{aligned} \quad (1)$$

where A is the m location sensors coordinates' aggregate.

Till now, we have formulated the location sensor distribution problem as an optimal design problem. Objective function and the constraint function is written as function (1), respectively. Fuzzy control or neural network method can be used to solve this nonlinear programming problem. Considering these methods need the path loss function $g(\lambda, \theta)$, which is not realizable to get on field. So in this paper we proposed the following Algorithm, which is practicable in the real system.

3 Optimization Algorithm

Path loss modelling provides an alternative to the empirical method for evaluating the path loss in the wireless system. There are two popular indoor path loss models for WLAN [7]. One slope model assumes a linear dependence between the path loss and the logarithm of the radio transmission distance. In this paper we use the Multi-wall model, which considered further attenuation term due to losses introduced by the walls and the floors [8]: $g(\lambda, \theta) = g_0 + 10\gamma \log(\lambda) + \sum_{i=1}^M g_i$ Here, g_0 is the reference loss value in dB for 1m. γ is the path loss exponent. g_i is wall loss factor for the i -th wall in dB. It is clear that $g(\lambda, \theta)$ is a convex function.

3.1 On Radial Optimal Algorithm

Use the AP as the center, location sensors are deployed on q radials, each adjacent radial has the angle of $2\pi/q$. m location sensors are averagely distributed on each radial, that is integer of m/q locations on one radial, denoted as $[m/q]$. We consider a random radial line θ_i to study the optimal method. The other radial line should has the same manner.

$S_i(g, \Delta)$ is the broken line interpolation function for $g(\lambda, \theta_i)$ by $\Delta: 0 = \lambda_0 < \lambda_1 < \lambda_2 < \cdots < \lambda_{[m/q]} < \lambda_{[m/q]+1} = \lambda_{max}$. We partition the Δ , so as to let $S_i(g, \Delta)$ to be the optimal uniform approximation function. That is: $\inf \|f - S_i(g, \Delta)\|_{[0, \lambda_{max}]} = \|f - S_i(g, \Delta^*)\|_{[0, \lambda_{max}]}$, where Δ is the all the partition possibility aggregate. The coordinates these λ_1 to $\lambda_{[m/q]}$ corresponding respectively are the location sensors on the radial θ_i optimized positions. We can prove that the above function is equivalent to:

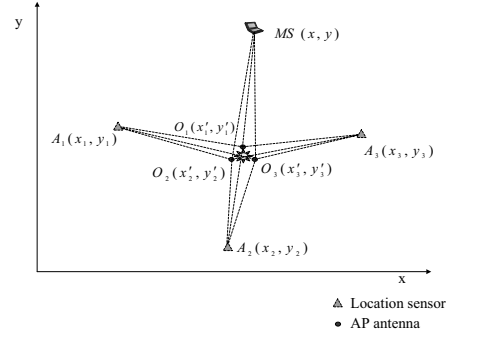


Figure 1: A location sensing deployment example.

Table 1: On Radial Optimal Algorithm

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Set  $\lambda_i^{(0)} = ih$ .  $h = \frac{\lambda_{\max}}{[\frac{m}{q}] + 1}$ ,  $i = 0, 1, \dots, [\frac{m}{q}] + 1$ .
Set  $\lambda_i^{(1)} = \lambda_{\max}$ ,  $i = 0, 1, \dots, [\frac{m}{q}] + 1$ .
Set  $\tilde{\lambda}_0^{(1)} = 0$ ,  $\tilde{\lambda}_{[\frac{m}{q}] + 1}^{(1)} = \lambda_{\max}$ .
if  $(\max\{|\lambda_i^{(1)} - \lambda_i^{(0)}|, 0 \leq i \leq [\frac{m}{q}] + 1\} > \epsilon)$ 
  set  $\lambda_i = \lambda_i^{(0)} \leftarrow \lambda_i^{(1)}$ 
  for  $i = 1 : 1 : [\frac{m}{q}]$ 
    if  $(e(\tilde{\lambda}_{i-1}^{(1)}, \lambda_i^{(0)}) = e(\lambda_i^{(0)}, \lambda_{i+1}^{(0)}))$  then
       $\tilde{\lambda}_i^{(1)} = \lambda_i^{(0)}$ 
    else
      set  $\tilde{\lambda}_i^{(1)}$  subject to  $(e(\tilde{\lambda}_{i-1}^{(1)}, \tilde{\lambda}_i^{(1)}) = e(\tilde{\lambda}_i^{(1)}, \lambda_{i+1}^{(0)}))$ ,
      where  $\tilde{\lambda}_{i-1}^{(1)} < \tilde{\lambda}_i^{(1)} < \lambda_{i+1}^{(0)}$ .
    end if
     $i++$ 
  end
end
for  $i = [\frac{m}{q}] : -1 : 1$ 
  if  $(e(\tilde{\lambda}_{i-1}^{(1)}, \tilde{\lambda}_i^{(1)}) = e(\tilde{\lambda}_i^{(1)}, \lambda_{i+1}^{(1)}))$  then
     $\lambda_i^{(1)} = \tilde{\lambda}_i^{(1)}$ 
  else
    set  $\lambda_i^{(1)}$  subject to  $(e(\tilde{\lambda}_{i-1}^{(1)}, \lambda_i^{(1)}) = e(\lambda_i^{(1)}, \lambda_{i+1}^{(1)}))$ ,
    where  $\tilde{\lambda}_{i-1}^{(1)} < \lambda_i^{(1)} < \lambda_{i+1}^{(1)}$ .
  end if
   $i++$ 
end
else
  set  $\lambda_i \leftarrow \lambda_i^{(1)}$ 
end
set  $\gamma \leftarrow \max\{e(\lambda_i^{(1)}, \lambda_{i+1}^{(1)}), i = 0, 1, \dots, [\frac{m}{q}] + 1\}$ .

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Table 2: Global Optimal Algorithm

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Set  $j$ , subject to:  $\gamma_j = \max\{\gamma_i, i = 1, 2, \dots, [\frac{m}{q}]\}$ .
Set  $k$ , subject to:  $\gamma_k = \min\{\gamma_i, i = 1, 2, \dots, [\frac{m}{q}]\}$ .
Set  $\delta_0 = \gamma_j - \gamma_k$ 
Set  $\delta_1 = 0$ 
loop
  if  $(\delta_1 \leq \delta_0)$ 
    set  $\delta_1 \leftarrow \delta_0$ 
     $n_j++$ ,
     $n_k--$ ,
    set  $j$ , subject to:  $\gamma_j = \max\{\gamma_i, i = 1, 2, \dots, [\frac{m}{q}]\}$ .
    set  $k$ , subject to:  $\gamma_k = \min\{\gamma_i, i = 1, 2, \dots, [\frac{m}{q}]\}$ .
    set  $\delta_1 = \gamma_j - \gamma_k$ 
    run On Radial Optimal Algorithm for radial  $j$  and  $k$ , respectively.
  end if
end loop
Set  $n_i, i = 1, 2, \dots, q$ 

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$\|f - S_i(g, \Delta^*)\|_{I_i^*} = \|f - S_i(g, \Delta^*)\|_{[0, \lambda_{\max}]}$, where $I_i^* = [\Delta_i^*, \Delta_{i+1}^*], i = 0, 1, 2, \dots, [\frac{m}{q}]$. This is the nonlinear equations. We design an iterate algorithm to solve the optimal approximate result. Here $e(\alpha, \beta) \triangleq \|f - l_{\alpha\beta}\|_{[\alpha, \beta]}$, $l_{\alpha\beta}$ is the line segment between α and β . We present this optimal algorithm in table [1]. ϵ is the given number which may effect the accuracy of the algorithm. γ is the maximum deviation. Next step, we use this parameter to optimize the location sensor number on each radials.

3.2 Global Optimal Algorithm

For each radial, by using the global Optimal Algorithm, we get $\gamma_i, i = 1, 2, \dots, q$. The algorithm is to optimize the maximum deviation on each radial to be most even. n_i denotes the location sensors number on radial i . Table [2] give the global optimal algorithm to optimize n_i .

4 Simulation

System simulations are done in network simulator OPNET. A typical office area is considered as our target area which has dimensions of 70m by 50m. Fig.2(left) gives the layout of the system structure in the office area. One AP, which has three separate antenna receiver, setup in the central area and totally 81 location sensors are uniformly distributed. The horizontal distance between two adjacent sensors is 6.84m, and their vertical distance is 5.72m. Fig.2(right) shows the system structure by

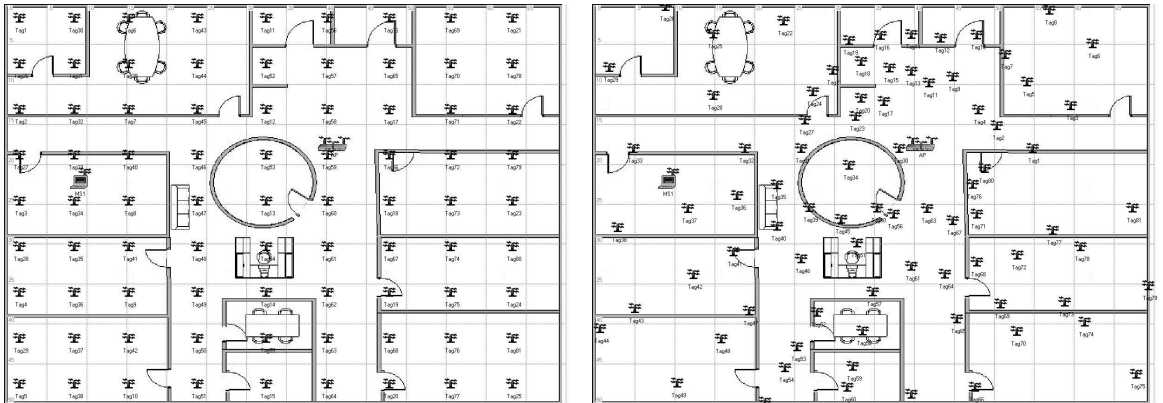


Figure 2: Uniformly distributed scenario(left) and optimal distributed scenario(right).

using the proposed optimal algorithm. The location sensors are been re-distributed on the 24 radials. In the simulation test, we take the cross-point of the horizontal and vertical dashed lines which contains totally 117 cross-points as the estimated points to compare the estimated accuracy.

Fig.3(left) compare the cumulative distribution function (CDF) of the error distances for these two

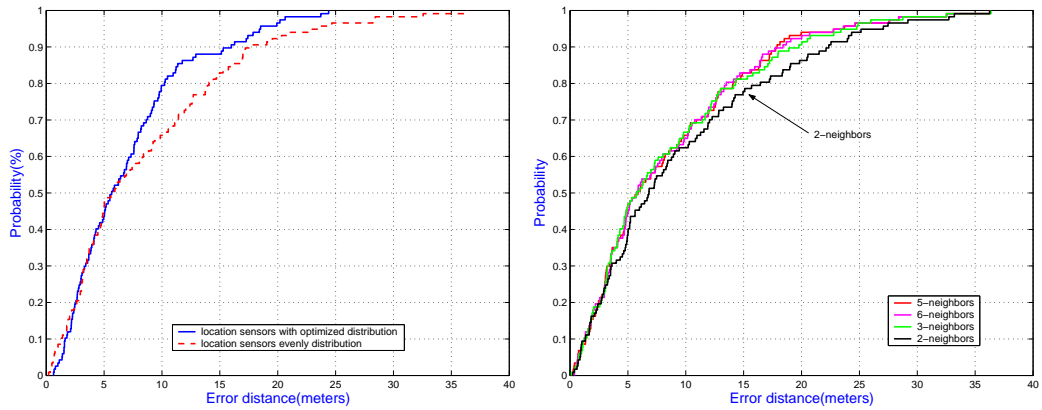


Figure 3: Two scenario compare(left) and k affect analysis(right).

scenarios. The Euclidean distance algorithm let $k = 4$, that is the algorithm select four nearest neighbor to calculate the estimated point coordinates. The result gives that the optimal scheme can significantly improve the system overall estimate accuracy. But for the different accuracy possibility, the improvement of the optimal scheme is not equally. In the optimal scenario, there is 79.49% probability that the location error distance will be within 10 meters, however, such probability will only be 65.74% when in the evenly distributed scenario. For 15 meters of location error distance, CDF of these two scenario is 88.03% and 82.91%, respectively. Observe to the CDF result below 5 meter, we can see these two scenario have the similar result.

In the simulation, we also try to find out what's the optimal number of location sensors k should be used in the positioning algorithm. Fig.3(right) shows the CDF of the error distance when different neighbor's number are used in optimal scenario. We choose the neighbour's number k from 2 to 6 and compute the error distance results, respectively. We find out that as the number k increases from 2 to 4, the positioning accuracy improves. With k continues increase from 4 to 6, the improvement of the location accuracy is not obviously. This observation indicates that, after a certain point, the positioning accuracy can't be improved by involving more the location sensors data in the positioning algorithm. In order to further increase the overall positioning accuracy, some other methods, such as adjusting the density of the location sensors, increasing the antenna precision maybe considered.

5 Conclusions

We analyzed the location accuracy effect by the tag distribution in the case that group antennas mounted in one AP. By theoretical analysis we get the optimized deploying scheme. Analytical results, verified by computer simulations, shows this scheme can significantly improve the location accuracy comparing to the evenly distributed methods, which is normally used. This scheme can also be used in other cellular location systems. The analysis method can also be applied for network planning and optimization.

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