FUZZY TOPOGRAPHIC MODELING IN WIRELESS SIGNAL TRACKING ANALYSIS

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Abstract: Fuzzy logic modelling can be applied to evaluate the behaviour of Wireless Local Area Networks (WLAN) received signal strength (RSS). The behavior study of WLAN signal strength is a pivotal part of WLAN tracking analysis. Previous analytical model has not been addressed effectively for analyzing how the WLAN infrastructure affected the accuracy of tracking. In this paper, we propose a novel fuzzy spatio-temporal topographic model. We implemented the proposed model with a large (9.34 hectare), built-up university, over 2,000 access points to survey and collect WLAN received signal strength (RSS). We applied the Nelder-Mead (NM) method to simplify our previous work on fuzzy color map into a topographic (line-based) map. The new model can provide a detail and quantitative strong representation of WLAN RSS. Finally, it serves as a quicker reference and efficient analysis tool for improving the design of WLAN infrastructure.

1 INTRODUCTION

Wireless Local Area Networks (WLAN) tracking analysis is a crucial part for deploying the efficient indoor positioning system. The analytical models can be used to visualize the distribution of signal and help to improve the design of positioning systems, for example by eliminating installation of WLAN access points (APs) and shortening the sampling time of WLAN received signal strength (RSS) in location estimation. The most typical techniques for locating WLAN enabled device are location-fingerprinting-based (LF-based). LF based method (Taheri et al., 2004)(J. Kwon et al., 2004)(K. Kaemarungsi and P. Krishnamurthy, 2004)(B. Li et al., 2005) locate a device by accessing a training database containing the location fingerprint to estimate the location. Location fingerprint (LF) is a set of the RSSs and coordinates in a region.

Recent research on WLAN RSS analytical model (K. Kaemarungsi and P. Krishnamurthy, 2004) and (N. Swangmuang and P. Krishnamurthy, 2008) are based on the accuracy of positioning systems and proximity graphs, such as Voronoi diagram, clustering graph. They assume the distribution of the RSS is in Gaussian and pair wise. Some research works (N. Swangmuang and P. Krishnamurthy, 2008), (M. B. Kjaergaard and C. V. Munk, 2008), and (S. Fang et al., 2008) ignores the radio signal properties. Such assumptions may ignore or distort the real behavior of RSS and provides inadequate and inaccurate RSS analysis. The fuzzy visualization map concepts widely applied in other fields, such as temperature, rainfall and atmosphere. Topographic mapping has been also highly recognized as a comprehensive method to visualize geographical information, such as the reflectance of slope and terrain. NM method also is used in many other fields such as data mining (S. Satapathy et al., 2007) and antenna optimization (B. Kolundzija and D. Olcan, 2003). Fuzzy, topographic and NM modelling could well be applied to modelling in WLAN RSS analytical model.

In this paper, we propose a novel analytical model that provides a visualization of the RSS distribution. We make use of the Nelder-Mead (NM) method to simplify our pervious works on the multi-layer fuzzy color model (C. L. Chan et al., 2008) to topographic (line-based) model. We develop a topographic model as analytical tools for evaluating and visualizing where the RSS is denser and clustering different RSS in different topographic level. The proposed model offers two benefits. First, it serves as a quicker reference and efficient analysis tool. Second, it can provide a detail and quantitative strong representation of WLAN RSS.

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The rest of this paper is organized as follows: Section 2 presents the topographic model design. Section 3 presents the experimental setup of large scale site RSS surveying in 9.34 hectare campus area over 2,000 access points. Section 4 discusses the analysis result of obstacles, human bodies and WLAN APs location. Finally, Sections 5 offers our conclusion and future work.

2 TOPOGRAPHIC MODEL DESIGN

The basic idea of topographic model is to plot a curve connecting minimum points where the function has a same particular RSS value. The sets of APs are known as topographic line nodes. Topographic line nodes are the APs residing on the topographic lines around contour region. In this section, we introduce the major operations of topographic model including propagation-based algorithm, fuzzy membership function in our previous work (C. L. Chan et al., 2008), topographic line node measurement, Nelder-Mead method and topographic model generation.

2.1 Propagation-based Algorithm

The propagation-based algorithm (K. Kaemarungsi and P. Krishnamurthy, 2004) which is used to calculate the RSS as follows:

$$r_i(d_{i,k}) = r_0(d_0) - 10\alpha \log_{10}(d_{i,k}) - wallLoss \qquad (1)$$

where $D = \{d_1 \ldots d_n \mid d_i \in \Re^n\}$ is a set of locations, $R = \{r_1 \ldots r_n \mid r_i \in \Re^n\}$ is a set of sampling LF vector respect to known d_i, α is the path loss exponent (clutter density factor) and *wallLoss* is the sum of the losses introduced by each wall on the line segment drawn at Euclidean distance $d_{i,k}$.

2.2 Fuzzy Membership Function

In this subsection, our fuzzy membership function has been published in (C. L. Chan et al., 2008) and we will make use of it. Nonetheless, for completeness in the following we briefly describe.

Using fuzzy logic, the proposed model offers an enhanced LF hyperbolic solution that maps the RSS from a 0 to 1 fuzzy membership function. Instead of using a numeric value, the fuzzy logic determines the RSS as "strong", "normal" and "weak".

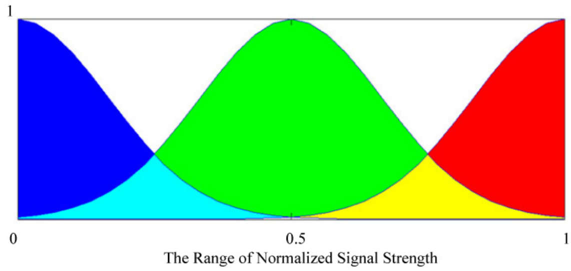


Figure 1: The RSS fuzzy membership graph.

The normalization distribution is used to represent the fuzzy membership functions.

$$P(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{(\alpha-\mu)^2}{2\sigma^2}}$$

where $p(x)$ is the probability function, x is the normalized RSS, σ is the standard deviation of normalized signal normalized strength in a region, μ is the mean of signal strength in a region. The WLAN network is fully covered for the whole campus.

The membership function of term set, μ(*RSSDensity*) = {*Red, Green,Blue*}. Red means the signal strength density is high, green means the signal strength is medium and blue means the signal strength density is low. The fuzzy set interval of blue is [0, 0.5], [0, 1] is green and [0.5, 1] is red.

For the blue region, σ = 0.5, μ = 0.

$$\mu_{Blue}(0 < x < 0.5) = \frac{2}{\sqrt{2\pi}} e^{-2x^2} \qquad (2)$$

For the green region, we substitute, σ = 0.5, μ = 0.5.

$$\mu_{Green}(0 < x < 1) = \frac{2}{\sqrt{2\pi}} e^{-2\left(x-\frac{1}{2}\right)^2} \qquad (3)$$

For the red region, σ = 0.5, μ = 1.

$$\mu_{\mathrm{Red}}(0.5 < x < 1) = \frac{2}{\sqrt{2\pi}} e^{-2(x-1)^2} \qquad (4)$$

Figure 1shows the fuzzy membership function. X-axis represents the normalized signal strength from 0 to 1 (from -93dBm to -15dBm). The width of membership function depends on the standard deviation of the RSS. The overlap area will be indicated by mixed colors. We can use different colored regions to represent the WLAN RSS distribution. Conceptually we define a spatio-temporal region as follows:

Assume that B is a finite set of RSS vector belonging to a particular color region, where $B = \{b_1 \ldots b_n \mid b_i \in \Re^n\}$, i.e., $b_i \in S$, $\forall S \in R$, and $\forall S \in [l,u]$, where l is the lower bound of fuzzy interval and u is a upper bound of fuzzy interval. To analyze the distribution surfaces S, there always exists a spatio-temporal mapping, $q : B \to S$.

$$q(x) = \int_S h(x) b(S) dS \tag{5}$$

where $h(x)$ is the characteristic function of S, i.e.,

$$h(x) = \begin{cases} 1 & x \in S, \quad (6a) \\ 0 & x \notin S \quad (6b) \end{cases}$$

and $b(S)$ is a weight function that specifies a prior on the distribution of surfaces S. We can explicitly define $b(S)$ by (1). By (2), (3), (4), (5) and (6), the RSS distribution can be illustrated.

2.3 Topographic Node

Each topographic node consists of three components and can be expressed as < *l, d, g* >, in which *l* represents topographic level, d represents the locations of WLAN received signal, g represents the gradient direction of the RSS distribution. The spatial data value distribution mapped into the (*x, y, l*) space, where the co-ordinate (*x, y*) represents the location and $l = f(x, y)$ describes a function mapping from (*x, y*) co-ordinates to level *l*. The gradient vector *g* denotes the direction of RSS where to degrade in the space. The gradient vector can be calculated by:

$$g = -f'(x, y) = \left(\frac{\Delta f}{\Delta x}, \frac{\Delta f}{\Delta y} \right)^T \tag{7}$$

2.4 Nelder-Mead Method

The Nelder-Mead (NM) method is a commonly used nonlinear optimization algorithm for finding a local minimum of a function of several variables has been devised by Nelder and Mead (J. Mathews and K. Fink, 1998). It is a numerical method for minimizing an objective function in a many-dimensional space. Instead of using (1) and (2), we estimate the location by NM method.

First, we collect the location fingerprint, *r* with an unknown location (*x,y*). We define $f(n)=|n-r|$, where n is any location fingerprint. Second, we select three location fingerprints (LFs) to be three vertices of a triangle.

We initialize a triangle *BGW* and function *f* is to be minimized. Vertices *B*, *G*, and *W*, where *f(B)* is the smallest value (best vertex), *f(G)* is the medium value (good vertex), and *f(W)* is a largest value (worst vertex). There are 4 cases when using NM method. They are reflection, expansion, contraction and shrink. We recursively use NM method until finding the point which is the local minimum (nearest) in *B*, *G*, *W* that they are the same value.

The midpoint of the good side is

$$M = \frac{B+G}{2} \tag{8}$$

2.4.1 Reflection using the Point R

The function decreases as we move along the side of the triangle from *W* to *B*, and it decreases as we move along the side from *W* to *G*. Hence it is feasible that function *f* takes on smaller values at points that lie away from W on the opposite side of the line between *B* and *G*. We choose a test point *R* that is obtained by "reflecting" the triangle through the side *BG*. To determine *R*, we first find the midpoint *M* of the side *BG*. Then draw the line segment from *W* to *M* and call its length *d*. This last segment is extended a distance *d* through M to locate the point *R* (See Figure 2). The vector formula for *R* is

$$R = M + (M - W) = 2M - W \tag{9}$$

2.4.2 Expansion using the Point E

If the function value at *R* is smaller than the function value at *W*, then we have moved in the correct direction toward the minimum. Perhaps the minimum is just a bit farther than the point *R*. So we extend the line segment through *M* and *R* to the point *E*. This forms an expanded triangle *BGE*. The point *E* is found by moving an additional distance d along the line joining *M* and *R* (See Figure 3). If the function value at *E* is less than the function value at *R*, then we have found a better vertex than *R*. The vector formula for *E* is

$$E = R + (R - M) = 2R - M \tag{10}$$

2.4.3 Contraction using the Point C

If the function values at *R* and *W* are the same, another point must be tested. Perhaps the function is smaller at *M*, but we cannot replace W with M because we must have a triangle. Consider the two midpoints C_1 and C_2 of the line segments *WM* and *MR*, respectively (see Figure 4). The point with the smaller function value is called *C*, and the new triangle is *BGC*. Note. The choice between C_1 and C_2 might seem inappropriate for the two-dimensional case, but it is important in higher dimensions.

$$C_1 = (M - W)/2 \tag{11}$$

$$C_2 = R - (M - W)/2 \tag{12}$$

2.4.4 Shrink toward B

If the function value at C is not less than the value at W, the points *G* and *W* must be shrunk toward *B* (see Figure 5). The point *G* is replaced with *M*, and *W* is replaced with S, which is the midpoint of the line segment joining B with W.

$$S = (B - W)/2 \tag{13}$$

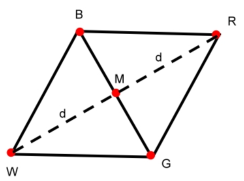


Figure 2: Reflection using the Point R.

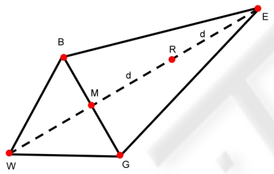


Figure 3: Expansion using the Point E.

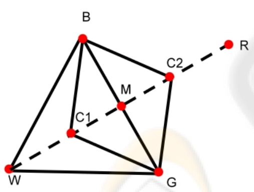


Figure 4: Constraction using the Point C.

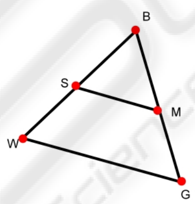


Figure 5: Shrink toward B.

2.5 Topographic Model Generation

We generate topographic model based on our previous work (C. L. Chan et al., 2008) and NM algorithm. We apply NM method to a many-dimensional RSS distribution space problem to simplify the fuzzy color map down to a contour (line-based) map.

First, we select three LFs to be three vertices of a triangle: $\vec{B}$, $\vec{G}$, and $\vec{W}$, where $\vec{B}$ is a location with high RSS (best vertex), $\vec{G}$ is a location with medium RSS (good vertex), and $\vec{W}$ is a location with the low RSS (worst vertex). The location vector of RSS at x_k, y_k use in function, *N(x, y)*. We use (1) to define *N(x, y)*. There are 4 cases when using NM method. They are reflection, expansion, contraction and shrink. We recursively use NM method until finding the point which is the local minimum in $\vec{B}$, $\vec{G}$, and $\vec{W}$ that they are the same value. Table 1 summarizes the procedure.

Table 1: Nelder-Mead Method Procedure.

IF *f(R)<f(G)*, THEN Perform Case (i) {either reflect or extend}
ELSE Perform Case (ii) {either contract or shrink}

BEGIN {Case(i).}	BEGIN {Case(ii).}
IF *f(B)<f(R)* THEN	IF *f(R)<f(W)* THEN
replace *W* with *R*	replace *W* with *R*
ELSE	ENDIF
compute *E* and *f(E)*	
IF *f(E)<f(B)* THEN	compute *C = (W + M)/2*
replace *W* with *E*	or *C = (M + R)/2* and *f (C)*
ELSE	IF *f(C)<f(W)* THEN
replace *W* with *R*	replace *W* with *C*
ENDIF	ELSE
ENDIF	compute *S* and *f(S)*
END {Case (i)}	replace *W* with *S*
	replace *G* with *M*
	ENDIF
	END {Case (ii)}

A contour function is then used to plot a curve connecting minimum points where the function has a same particular value. We normalize the minimum value between 0 and 1, and the contour line is 0.1 in each level.

3 EXPERIMENTAL SETUP

In this section, we describe experiment setup in 9.34 hectare campus area. We use the same setting as used in (J. Kwon et al., 2004), (R. Jan and Y. Lee, 2003), (Taheri et al., 2004), (K. Kaemarungsi and P. Krishnamurthy, 2004), (K. Kaemarungsi and P. Krishnamurthy, 2004), (W. Wong et al., 2005) and (P. Bahl et al., 2000). RSS site survey measurement will be in The Hong Kong Polytechnic University (PolyU) campus. The approximate total area of the campus is 9.34 hectare. A standard laptop computer equipped with an Intel WLAN card and client manager software was used to measure samples of RSS from access points (APs) of PolyU campus.

The WLAN card is chipset inside the laptop.

There are basically 26 buildings from Core A to Core Z and 7 extra buildings with WLAN access. Each core building is covered by at least 13 APs. The radio frequency (RF) channels of IEEE 802.11b are in the 2.4 GHz band which is shared by other equipment in the industrial, scientific, and medical (ISM) band such as Bluetooth. The number of non-overlapping channels for 802.11b is three. We observe that the RSS value reported by the WLAN card is an average value over a sampling period and in integral steps of 1 dBm. The received signal sensitivity of the WLAN card also limits the range of the RSS to be between -93 dBm and -15 dBm. Nevertheless, the highest typical value of the RSS is approximately -30 dBm at one meter from any AP. The sampling schedule is to collect the RSS data every 5 seconds. The vector of RSS data at each location forms the location fingerprint with around 20 RSS elements in the vector. Total 27 locations of measurement are chosen in the campus.

Figure 6 and 7 show the 27 locations site plan. The radio channels used for each AP are channel 1, 6, and 11 respectively. The sampling will be taken with two periods of time, (7:30am-9:30am (leisure) and 4:30pm - 6:30pm (busy)). From (K. Kaemarungsi and P. Krishnamurthy, 2004), the presence or absence of people in the building significantly affects the RSS values. The data were collected four times with four different directions, North, South, East and West. The duration of sampling was 2 weeks with total 12 days (from Mon to Sat). In mean while, temperature, weather, sampling time and humidity were recorded. The total number of RSS samples would be 12 days X 4 directions X 27 buildings X 20 APs X 2 times = 51840.

Figure 6: The satellite photo of PolyU campus from Google Earth.

For 27 locations on the floor, we collected environmental readings at these locations over two-week period of time. At each testing location, we picked a frequency 2.4GHz and calculated their average amplitude respectively. Note that the RSS is the received signal from a beacon packet, while the spectrum energy is the ambient RF energy corresponding to a specific frequency range. Table 2 summaries the campus area measurement setup

Figure 7: The site plan for PolyU Campus with 27 buildings.

Table 2: Summary of Experiment Setup in PolyU Campus.

Item	Description
Total campus area	9.34 hectare 26 core + 7 extra buildings
Sampling period	2 weeks 7.30am - 9.30am 4.30pm - 6.30pm
RSS variation	Between -93 dBm and -15 dBm
No. of sample points	51,840 sample points
WLAN channel	1, 6, and 11
Facing direction	North, South, East, and West

4 DISCUSSION AND ANALYSIS

In this section, we discuss the effect of the presence of human and LOS factor in our topographic model. There are three RSS features to be analyzed, LOS, the presence of human and RSS variation.

4.1 Effect of LOS on RSS

Figure 8 and 9 show the effect of LOS in two major clusters of RSS. The two major centers of high intensity locate at F core and S core.

The distance between F core to S core buildings is around 600m apart. The RSS should be covered evenly. Moreover, between M core (Lee Ka Shing

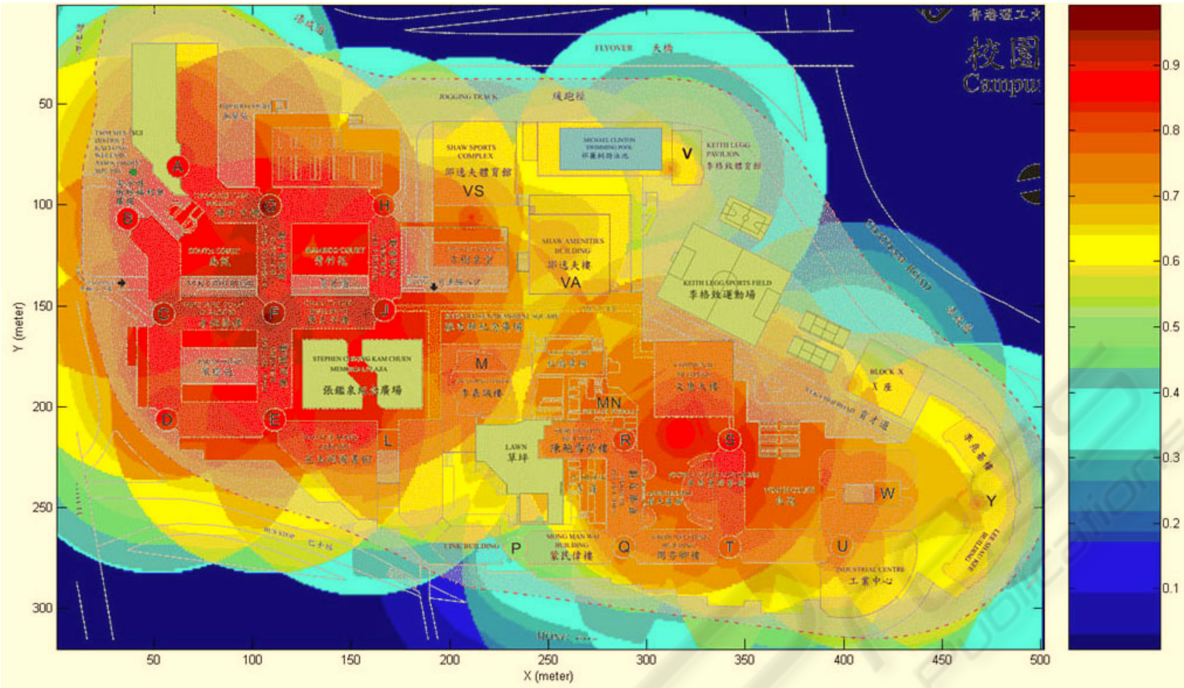


Figure 8: Fuzzy RSS Distribution with the campus floor plan.

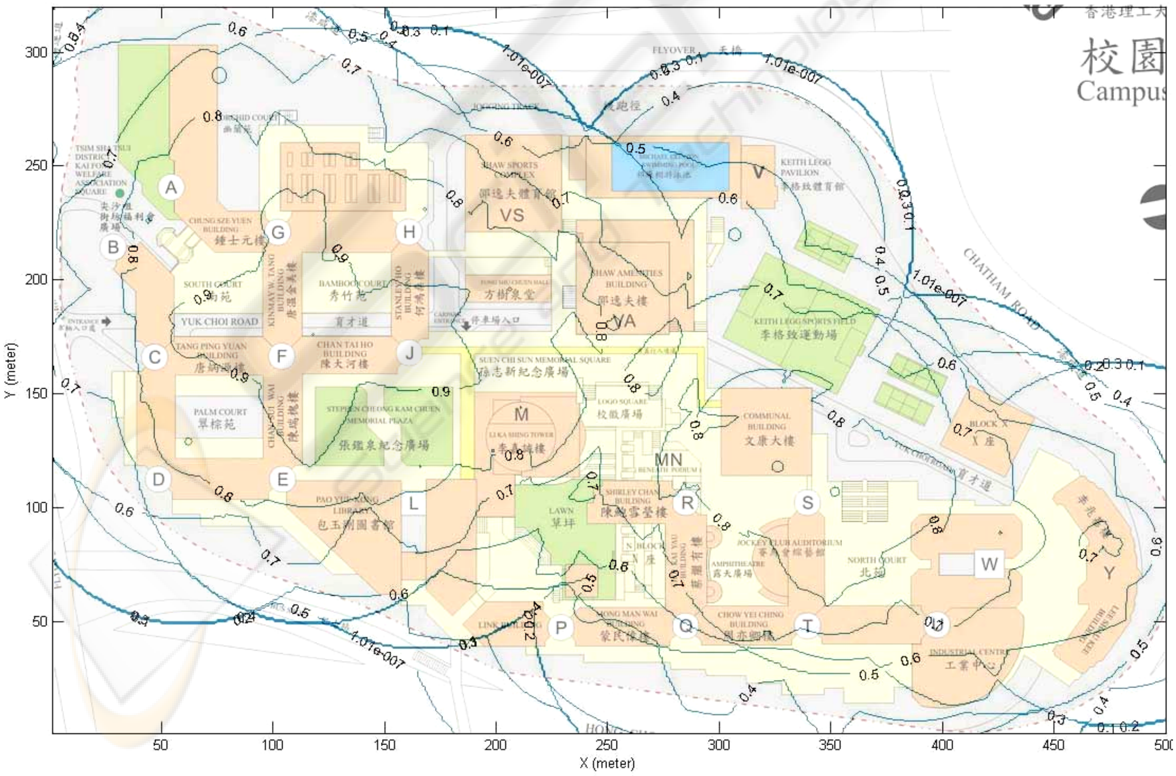
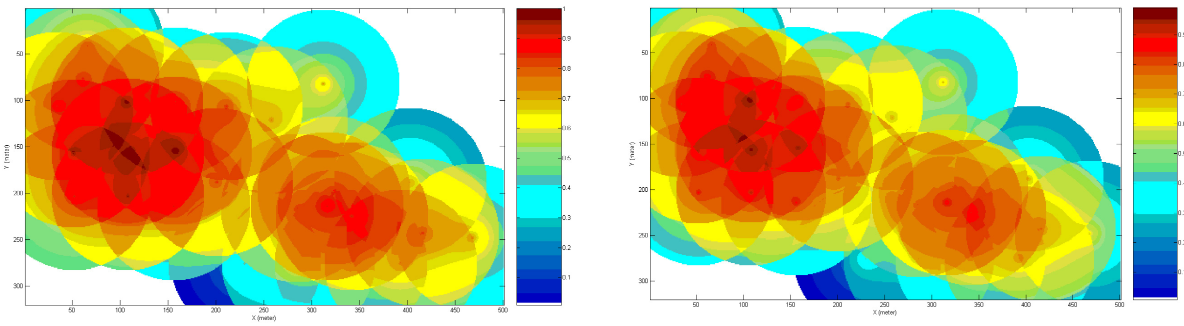
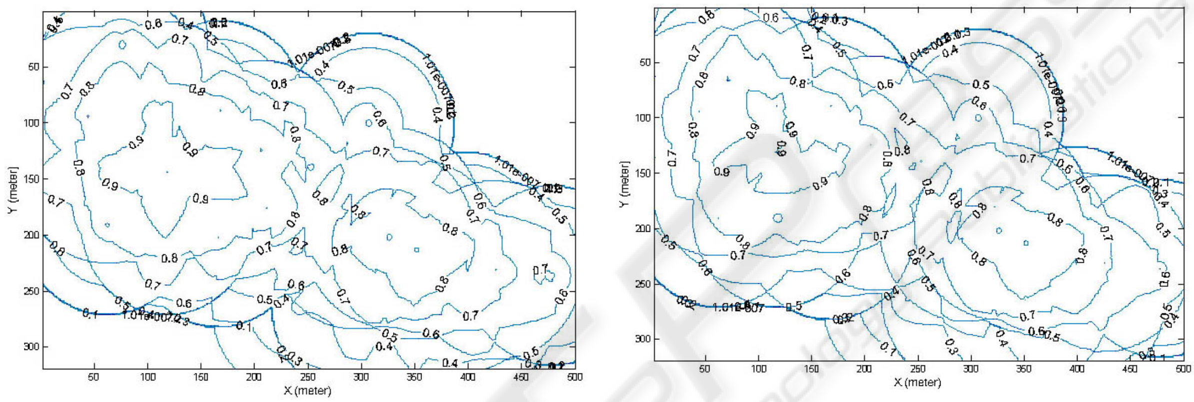


Figure 9: Topographic RSS Distribution with the campus floor plan.



(a) In the leisure morning period (b) In the busy evening period

Figure 10: RSS Distribution in Fuzzy Analytical Model.



(a) In the leisure morning period (b) In the busy evening period

Figure 11: RSS Distribution in Topographic Model.

Tower) to R core buildings (Shirley Chan Tower), the RSS distribution is relatively low. The heights of two buildings in M core and R core are around 80m and 70m respectively. The distance between M to R core is around 200m apart.

As we can see the topographic map in Figure 11a and 11b, the slope of contour line from M core to R core is steep in the edge area, it means that the RSS is weaken quickly in the middle from M core to R core due to NLOS effects. For LOS conditions, RSS should fit into log-normal distribution. A multi-story building in a campus area will experience lower signal strengths within tall buildings due to the absence of LOS propagation.

4.2 Behavior Study on the Human's Presence

As the previous section mention, we collected the RSS data in 2 periods, one is in the morning leisure period (7.30am-9.30am) and the other is in the busy evening period (4:30pm - 6.30pm). We would like to observe the difference between two periods. Figure 10 and 11 show the difference RSS pattern which the RSS collect in the two different time slot. We can see that there is significant change of the RSS value. Figure 11a shows the topographic region in 0.9 level is larger than Figure 11b. We can observe the slope on Figure 11b degrades larger than Figure 11a. As a result, it verifies the effect of the user's presence can affect the mean of the RSS value.

4.3 Effect of the RSS Variation on Accuracy

The accuracy of the tracking system is highly dependent on RSS variation. If the standard deviation of the RSS increases, the accuracy of the tracking system falls. To maintain high accuracy, the suggested standard deviation of RSS should be under 4dBm in this paper. (Elsewhere, a standard deviation of 2.13dBm has been assumed. (Taheri et al., 2004)) However, as the standard deviation depends on the real environment, including the density of human traffic, in some situations the standard deviation will be large.

5 CONCLUSIONS

In this paper, we propose NM optimized topographic model for RSS distribution. The new model provides quicker references and efficient analysis tool for improving the design of WLAN infrastructure to achieve localization accuracy. In our university site experiment, we provide a spatial analytical model for WLAN tracking in a campus. The fuzzy topographic RSS analytical map provides easier understanding of WLAN RSS pattern in a region. The usage of model can improve the efficiency usage of WLAN infrastructure substantially. Future work will consist in building a 3D pervasive tracking and a dynamic spatio-temporal filtering technique.

REFERENCES

Taheri, A. Singh, and A. Emmanuel, 2004. Location fingerprinting on infrastructure 802.11 WLAN local area networks (WLANs) using Locus. Proceedings of the 29th Annual IEEE International Conference on Local Computer Networks, pages 676–683.

J. Kwon, B. Dundar, and P. Varaiya, 2004. Hybrid algorithm for indoor positioning using WLAN LAN. Vehicular Technology Conference, 2004. VTC2004-Fall.

K. Kaemarungsi and P. Krishnamurthy, 2004. Modeling of indoor positioning systems based on location fingerprinting. INFOCOM 2004. Twenty-third AnnualJoint Conference of the IEEE Computer and Communications Societies, 2, 2004.

B. Li, Y.Wang, H. Lee, A. Dempster, and C. Rizos, 2005. Method for yielding a database of location fingerprints in WLAN. Communications, IEE Proceedings-, 152(5):580–586, 2005.

N. Swangmuang and P. Krishnamurthy, 2008. Location Fingerprint Analyses Toward Efficient Indoor Positioning. Sixth Annual IEEE International Conference on Pervasive Computing and Communications, 2008, pages 101–109, 2008.

M. B. Kjaergaard and C. V. Munk, 2008. Hyperbolic Location Fingerprinting- A Calibration-Free Solution for Handling Differences in Signal Strength. Sixth Annual IEEE International Conference on Pervasive Computing and Communications, 2008, pages 110–116, 2008.

S. Fang, T. Lin, and P. Lin, 2008. Location Fingerprinting In A Decorrelated Space. Knowledge and Data Engineering, IEEE Transactions on, 20(5):685–691, 2008.

S. Satapathy, J. Murthy, P. Reddy, V. Katari, S. Malireddi, and V. Kollisetty, 2007. An Efficient Hybrid Algorithm for Data Clustering Using Improved Genetic Algorithm and Nelder Mead Simplex Search. Conference on Computational Intelligence and Multimedia Applications, 2007. International Conference on, 1, 2007.

B. Kolundzija and D. Olcan, 2003. Antenna optimization using combination of random and Nelder-Mead simplex algorithms. Antennas and Propagation Society International Symposium, 2003. IEEE, 1, 2003.

C. L. Chan, G. Baciu, and S. C. Mak, 2008. WLAN Tracking Analysis in Location Fingerprint. to appear in the IEEE WLAN and Mobile Computing, Networking and Communications, 2008.

K. Kaemarungsi and P. Krishnamurthy, 2004. Properties of indoor received signal strength for WLAN location fingerprinting. Mobile and Ubiquitous Systems: Networking and Services, 2004. MOBIQUITOUS 2004. The First Annual International Conference on, pages 14–23, 2004.

R. Jan and Y. Lee, 2003. An indoor geolocation system for WLAN LANs. Parallel Processing Workshops, 2003. Proceedings. 2003 International Conference on, pages 29–34, 2003.

W. Wong, J. Ng, and W. Yeung, 2005. WLAN LAN positioning with mobile devices in a library environment. Distributed Computing Systems Workshops, 2005. 25th IEEE International Conference on, pages 633–636, 2005

P. Bahl, V. Padmanabhan, and A. Balachandran, 2000. A Software System for Locating Mobile Users: Design, Evaluation, and Lessons. online document, Microsoft Research, February, 2000.

Taheri, A. Singh, and A. Emmanuel, 2004. Location fingerprinting on infrastructure 802.11 WLAN local area networks (WLANs) using Locus. Proceedings of the 29th Annual IEEE International Conference on Local Computer Networks, pages 676-683, 2004.

J. Mathews and K. Fink, 1998. Numerical Methods Using MATLAB. Simon & Schuster, 1998.