Research Journal of Applied Sciences, Engineering and Technology 4(18): 3344-3347, 2012
ISSN: 2040-7467

Submitted: March 10, 2012 Accepted: April 08, 2012 Published: September 15, 2012

Where Am I in Wi-Fi?-An Experimental study

[1]M. Hemalatha, [2]V. Prithviraj, [3]S. Jayalalitha and [4]G. Manikandan
[1,4]School of Computing, SASTRA University, Tamil Nadu, India-613401
[2]PEC, Puducherry, India-605014
[3]School of EEE, SASTRA University, Tamil Nadu, India-61340

Abstract: Location identification is an essential area of study in ubiquitous computing. The IEEE 802.11 Wi-Fi network is the pioneer in the arena of short range wireless systems and its utility is observed in many domains. This paper elegantly depicts the idea of a localization technique intertwined in Wi-Fi network to facilitate roaming of wireless nodes. The RSSI measurement is carried out with respect to the APs and rules are demarcated for the initial condition. A data base is created and streamlined with the existing rules and rank entries and location is assessed for a specific node of interest. This report expounds the results observed in an Engineering institution where approximately 500 APs are mounted around the campus. The context parameter observed is the location of a client with average signal strength of 75mV.

Keywords: AP localization, RSSI, SSID, Wi-Fi,

INTRODUCTION

Location of an end user or relevantly, the wireless device is useful information in any context to know the interest of the user, device identification, user identification and tracking. This could be realized in many ways through sensors, Radio Frequency Identification (RFID) technique, RADAR systems, image recognition, etc. In most of the types enumerated earlier, they should possess an infrastructure to collect and broadcast details to the observer or the central server. For small or medium scaled campus where the wireless connectivity exists through the Wi-Fi Access Point (AP), it would be better to exploit the vicinity of signal for localization. Technologies like GPS, location mindful services are few specimens which exemplify the need for location awareness. Now, there are various methods to know one's position. Foremost of which is triangulation. This approach works well for an organized mesh of access points which is dense but quite obsolete otherwise. Another method is to use RFID tags. This process is very effectual but requires us to use an external agent, the RF tag. While RFID tags are exceptionally accurate, it holds genuine only in a limited environment (Up to 100 m max). This limitation of RFID tags coupled along with its compulsion to mount a RFID tag render its use and framework a little overpriced and dependent on the sound working of the tag. Triangulation on the other hand is efficient in places where access points are set up in a close grid and the received signal strength does not oscillate too much. An exploration into the above procedures gives us a picture of what are the deterrent factors in constructing a good localization system. Many researches are underway to make higher level context inferences based on location. Different kinds of localization techniques have been demonstrated with various wireless technologies such as the Cellular system (Mike *et al*., 2006), Global Position System (GPS) (Bulusu *et al*., 2000), Bluetooth, WiFi and RFID. Location estimation by Bayesian Filtering Technique is detailed by (Dieter *et al*., 2003). Each of these techniques possesses its own share of strengths and weakness. When a detailed survey is made, one could conclude that the Wi-Fi-based location is by far the most superior technique for indoor and outdoor identification principally due to its long coverage area as a result of the popularity of APs in many organizations. In comparison, the GPS is limited with poor signal strength in indoor measurement, Blue tooth is only for short range convergence, RFID and Cellular system is subservient because of the accuracy and additional infrastructure requirement.

The location of the client can be found with median error of 1.5 meters and status(motion or stationary) of the device with the user may also be found with LOCADIO system, which uses Wi-Fi signal strengths as the measuring parameter. But the method adopted to give 87% accuracy is a prolonged procedure (Krumm and Horvit, 2004). A simple localization process proposed in this paper uses the table entries and the logical information to reveal the accurate place of component. Static Rule-Based Localization Method (SRLM), Static Rule-Based Backtracking Method (SRBTM), Static Rule-Based HMM Method are compared with WHAM! (Lee and Chen, 2007) and LOCADIO and is concluded that the rules based measurement is the most accurate technique (Qiuxia *et al*., 2008). Numerous kinds of projects were done based on matching of Wi-Fi RSS by comparing the current RSS at the client with the RSS in

Corresponding Author: M. Hemalatha, School of Computing, SASTRA University, Tamil Nadu, India-613401

the server database (Xiang *et al*., 2004). Localization techniques require a well defined representation of spatial knowledge and can be categorized into geometric and symbolic models. The symbolic models for location Navigation in Mobile Environment are instrumented and proposed to a large scale network with dynamic topology (Haibo and Dik-Lun, 2004). A proxy reference point plays the role of representing the dynamically changing channel parameters between AP and the mobile node in WLAN scenario, but the performance gets saturated once it reaches a threshold and the deployment of APs does not have much effect on the error rate as long as they retain a distance from each other (Injun *et al*., 2011). Specific RSS Signature Modeling for Wi-Fi Localization was proposed which exploits site-specific information to impart a tighter fit to the empirical RSS signatures and was observed that the behavior of the RSS signatures is reliant on the location of the AP with a building due to shadow fading (Brian and Kaveh, 2009). Finger print algorithm provides more accurate results but mandatory to be reoriented when new nodes are appended (Yu-Chung *et al*., 2005), a scalable finger print algorithm proposes a method which does not require a retraining stage (Le *et al*., 2011), but these schemes needed conversion of signal strengths. Factors affecting Wi-Fi localization are range, self sufficiency, erratic signal readings and sparse number of visible access points and change of infrastructure. An effortless rule based Wi-Fi localization scheme projected in this paper provides more accuracy and direct substitution of signal strength in the table to assign weights and for dynamic update of weight factor based on the RSSI (Received Signal Strength Identification) and SSID (Service Set Identifier). The correlation between adjacent signal strength (RSSI) shows how the method overcomes the above mentioned limiting factor.

METHODOLOGY

Proposed scheme: The proposed rule based localization method is based on two basic conjectures made upon observation. Firstly, even if the absolute signal strength observed at one access point at given point may differ with time; the relationship between two access points visible at the same point does not change. Secondly, the proximity of an access point to a particular point is directly proportional to its frequency of visibility at that point. Having said these, the position is finally calculated using the combination of a quantitative and qualitative method and by elimination of relatively improbable locations. A number of points are elected based on certain parameters and are referred as calibration points. Once these points are chosen, a laptop is taken to that point and the current values of the signal strengths pertaining to every access point visible in the calibration area are recorded. Then, based on these values, rules are formulated. Rules carry information about the comparison of strength of signals from two distinct access

Table 1:

Access point -1	75
Access point -1	…
Access point -1	…
Access point -1	80

Table 2:

Mac	Max	Min	Average	Count
Mac-1	80	75	78	25

Table 3:

Ap -1	Ap – 2	Rule type
Mac -1	75-77- 80	V

Table 4:

.Mac	Max	Min	Average	Count
Mac-1	80	75	78	25
Mac -2	76	70	72	27

points. Thus after the readings in calibration points have been taken, the system is ready to function. To determine the position, signal strength readings are taken at that point. Then the locality is determined. Then rules are formed for the observed signal strength. These rules are matched with the rules for calibration points located in that locality. Based on the probability of each point, the final location is confirmed. This scheme is implemented in the following three phases:

- Training
- Reading
- Location determination

Training phase: In the training phase, rules are formed based on signal strength readings and a set of rules define a place. When the laptop is trained at a calibration points, the system records 30 sets of values which are recorded at a difference of 500 milliseconds to account for fluctuations in signal strength. Once they are recorded and then tabulated as in Table 1.

For the experimental evaluation 30 such readings are recorded. In a separate table the following data are inserted. Access point mac-id, number of readings out of 30 it appears, its maximum and minimum and average signal strength readings out of the 30 readings.

The Table 2 can be understood as following. Access point with mac id = mac-1 (just a random name) appears 25/30 times the readings were taken. The maximum value recorded was 80 and minimum was 75, averaging at 78. Two kinds of rules can be followed as value based rules and comparison based rules. Value based rules are those rules that depict only one access point and is described in Table 3.

Rule type 'V' denotes value based rule, AP -2 looks like this: 75-77-80' where 75 is the minimum value, 77 is average value and 80 is the maximum value. Comparison rules view the relationship between two access points observable at the calibration point. The entry details and the descriptions are shown in Table 4 and 5, respectively.

Table 5:

Ap -1	Ap - 2	Rule type
Mac -1	Mac -2	>

Table 6:

RANK1	RANK2	R1+R2	R1-R2

The observation made from the above sample entry is that ap1 > ap2 i.e., the average signal value of ap1 > ap2. Thus, after the rules are framed, they are streamlined into the database corresponding to this calibration point and its co-ordinates and details. The rules also sustain information called rank, weight, rank-weight. These are calculated as below. The weight average of each individual access point is calculated as follows:

$$weight = \frac{No. of\ appearance of\ AP}{Max. No. of\ appearance of\ any\ AP}$$

And weight for value based rule is the same as its Access point. Weight for a comparison rule is the multiplication of weights of the two access points involved. Rank is allotted on a similar basis. The access point for one calibration point gets maximum rank if the count is the maximum. If there is a clash of count, the AP with the higher signal strength gets the higher rank. And rules are formed by the method shown in Table 6.

For a comparison rule, the above table is constructed. Rank1 and rank2 are the ranks of the respective APs. Firstly the table is arranged in decreasing order of R1+R2. Then, if there is clash of values, the records concerned are arranged in decreasing order of R1-R2 because, if this is lesser, the ranks are more or less nearer, thus giving a better result. A rank-weight is weight given to a rule based on rank approach.
Rank-weight for a particular rule is:

$$1 - \frac{Rank}{Sum of\ Ranks}$$

Thus a rule with a greater rank procures a greater rank-weight.

In reading phase, the signal is read from the remote end device: It's to be noted that all the details about the calibration points, the rules and such information is located in a centralized server. This segment of the process is executed in the disconnected phase, in the target device whose location is to be found. A background process is mounted in the target systems, which executes this when prompted by the server. The program records 30 values in a 200 ms interval. Then rules are formulated according to this data.

Location determination: After the incoming rules have been determined, it is possible to verify the location. Firstly, the sub-location i.e., building where most of the APs are located is finalized. Then, each of the incoming rules is matched with every rule corresponding to all calibration points in that sub-location. Two sets of probabilities are calculated.

Method I:

- All the rules that satisfy the comparison rules observed are determined in each calibration point.
- The rules are multiplied with their respective weights.
- The sum of these is divided by the sum of weights of all comparison rules in that particular calibration point irrespective of whether it is satisfied or not.
- Denoted P1:

$$P1 = \frac{Satisfied\ Comparison rule\ X\ its Weight}{Every Comparison rule\ X\ its Weight}$$

- For value rules, its calculated like:

$$P2 = \frac{Avg_{observed} - Avg_{recorded}}{Max_{recorded} - Min_{recorded}}$$

But if the difference between both averages is 0, probability is 1:

- P1 + P2 is recorded for every calibration point.

Method II:

- P2 is calculated in a similar manner as method 1
- P1 is also calculated in the same way as in method 1 but use of weight is replaced by use of rank-weight
- P1+P2 is recorded for every calibration point

Using method 1, the points with top 3 probabilities are noted. Similar manner is performed by method 2. A consolidated list of the two is made. Two points, whose distance is the least, are chosen from the consolidated list. The average of the two co-ordinates is determined and thus location is finalized.

RESULTS AND DISCUSSION

This system was experienced in three different buildings with 2 or more floors. Various results were observed and listed. In a building, where the number of visible points was minimal and in the building where visible AP was very high, results ± 10 m were observed. On the contrary, in a building where an average number of APs observed were 4, results were as close as ± 5 m. This led to the inference that, this practice delivered its best under architecture with one or two access points per floor.

CONCLUSION AND FUTURE SCOPE

As the comprehension of one's location is of prime importance in present and future computation technologies, this simple rule based scheme, worked successfully for a small scale WLAN network and provided a straightforward way to trace any user and a wireless node in the environs of the network coverage giving the lead of simple localization of nodes with the existing network infrastructure. This effort could be further lengthened to perceive the eminence of the wireless end user as in motion or stable and also to facilitate automatically when APs are added, removed or relocated. For future research, it could be extended to develop new approaches for Wi-Fi localization and to enrich the procedures by expediting automatic updates of rules when APs are added, removed or relocated.

ACKNOWLEGEMENT

We thank our management for permitting us to conduct experiment in our 250 Mbps, Wi-Fi enabled campus network.

REFERENCES

Brian, R. and P. Kaveh, 2009. Site-Specific RSS Signature Modeling for WiFi Localization Global Telecommunications conference, (GLOBECOM 2009), pp: 1-6.

Bulusu, N., J. Heidemann and D. Estrin, 2000. GPS-less low-cost outdoor localization for very small devices. IEEE Person. Commun., 7(5): 28-34.

Dieter, F., H. Jeffrey, L. Lin, S. Dirk and B. Gaetano, 2003. Bayesian Filtering for Location Estimation. IEEE Pervasive Computing, IEEE Computer Society Press, July-September, University of Washington, Seattle, WA, USA. 2003. 2(3): 24-33.

Haibo, H. and L. Dik-Lun, 2004. Semantic location modeling for location navigation in mobile Environment", International Conference on Mobile Data Management (MDM '04'), pp: 52-61.

Injun, P., B. Wonsun and C.K. Yong, 2011. Hidden markov model based tracking of a proxy RP in Wi-Fi Localization. Vechiluar Technology Conference (VT spring), pp: 1-5.

Krumm, J. and E. Horvit, 2004. LOCADIO: Inferring motion and location from Wi-Fi signal strengths, First International Conference on Mobile and Ubiquitous Systems: Networking and Services, (MOBIQUITOUS 2004), pp: 4-13.

Lee, D.L. and Q. Chen, 2007. A model-based wifi localization method. in Info scale 07 The Third International ICST Conference on Scalable Information Systems, ACM.

Le, D., T. Nam and Nguye, 2011. A scalable Wi-Fi based localization approach truc. 2011. International Conference on Advanced Technologies for Communications (ATC 2011), pp: 131-134.

Mike, Y.C., S. Timothy, C. Dmitri, H. Dirk, H. Jeffrey, H. Jeff, L. Anthony, P. Fred, S. Ian and V. Alex, 2006. Practical Metropolitan-scale Positioning for GSM Phones, In Proceedings of the Eighth International Conference on Ubiquitous Computing (Ubicomp 2006), pp: 225-242.

Qiuxia, C., L. Dik-Lun and L. Wang-Chien, 2008. Rule based wifi localization methods. IEEE/IFIP International Conference on Embedded and Ubiquitous Computing, pp: 252-258.

Xiang, Z., S. Song, J. Chen, H. Wang, J. Huang and X. GAO, 2004. A wireless lan-based indoor positioning technology. IBM J. Res. Dev., 48(5.6): 617-626.

Yu-Chung, C., C. Yatin, L.M. Anthony and K. John, 2005. Accuracy characterization for metropolitan-scale Wi-Fi localization. In Proceedings of Mobisys.