Implementation of Wi-Fi Based Location Tracking System Based on Signal Strength Measurement and Artificial Neural Network

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Abstract
Radio frequency signals are present everywhere and almost at any time, from GSM mobile phones to wireless devices. Wi-Fi enabled devices can be located within the area of deployment. A location system that takes advantage of the availability of these signals and the received signal strength indicator (RSSI) measured by these mobile devices was developed using Wireless Fidelity (Wi-Fi) as access points (APs). The concept of Artificial Neural Network (ANN) was applied to the location system for computation of location coordinates. This allows for tolerance and generalization of results. Location information of target devices was made available via a web interface. The user had the option of selecting registered device in a location database server using Media Access Control (MAC) address of their tag and the computed location is displayed on a floor plan of the building.

Keywords: Wi-Fi, RSSI, ANN, RTLS, RFID, AP, WLAN.

1. Introduction

With the rapid development of mobile computing devices and wireless local area networks (WLAN), more and more attention is drawn to location-aware systems and services [1]. Rapid advances in wireless technologies and the near ubiquitous nature of portable mobile devices provide an opportunity to develop and deliver new types of location centric applications and services to users [2]**.** Real Time Locating Systems (RTLS) continuously determine and track the real-time location of assets and personnel. Since its inception almost ten years ago, the RTLS technology has now become a viable solution for tackling the business challenges of determining the location of assets and people. Radio frequency signals are present everywhere and almost at any time, from GSM mobile phones to wireless devices. Wi-Fi tags are a variation of RFID tags that use wireless communication for location. RFID is a rising technique for identification and authentication, and some researchers adapt it for in-building positioning by measuring the angle and time of the RF signals arriving at 3 – 5 RFID readers [3]. RFID systems usually consist of RFID tags and RFID readers. These tags are intelligent barcodes that can talk to a networked system to track any object it has been placed on. The operation of the system is based on strategically located RFID readers placed around a building identifying RFID tags with unique identifiers attached to objects or persons as they pass by the readers. RFID readers then communicate with a gateway or server that stores the location of tags so that these locations may then be queried. M.J.Callaghan et al, presented an indoor positioning system architecture based on a combination of wireless sensor networks and RFID technology [2]. The approach used integrates RFID readers connected to endpoint nodes of a wireless sensory network to track and locate mobile objects with RFID tags attached as shown in Figure 1. The RFID readers were incorporated into the wireless sensor networks to provide a means of network communication, but in actual fact, readers' function only to read the location of RFID tags. Of course, it would be more cost effective to eliminate the use of RFID readers. There have been recent approaches of implementing RFID technology over wireless infrastructure using the wireless access points (APs) to serve as tag readers. This technique eliminates the need to have a separate intrusive network for running the RFID infrastructure. Wireless fidelity, a wireless communication technology that provide connections between portable computers and wired connections to the Internet [4].

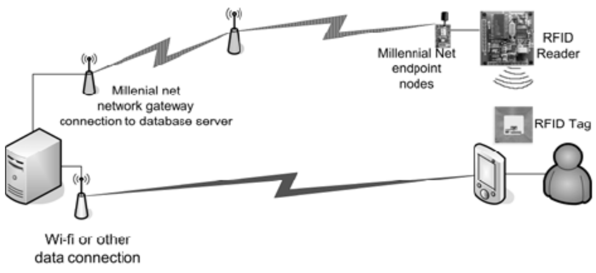

Figure 1: High Level Network Model of the System

Wi-Fi is now being put to use in location based systems since most buildings, offices, and organizations have pre-existing wireless infrastructure. Yibo Chen and Rong Luo, presented a Wi-Fi-based Local Locating System (Wi-Fi-LLS) which used Wireless LAN- (Wi-Fi) access points (AP) as LLS readers. The system consists of three main parts: Wi-Fi tags, AP, and Data server as illustrated in Figure 2 below:

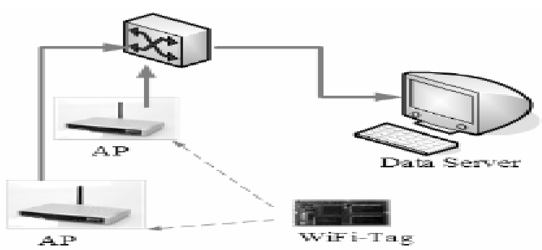

Figure 2: Overview of Wi-Fi Local Locating System

This work eliminates the need for these readers and instead use, Wireless Fidelity (Wi-Fi) access points (APs) and takes advantage of the availability of these signals and the received signal strength indicator (RSSI) measured by mobile devices. The Wi-Fi-based location tracking system consists of three main parts: the Wi-Fi clients, the Access points (APs), and the Data Server as shown in Figure 3.

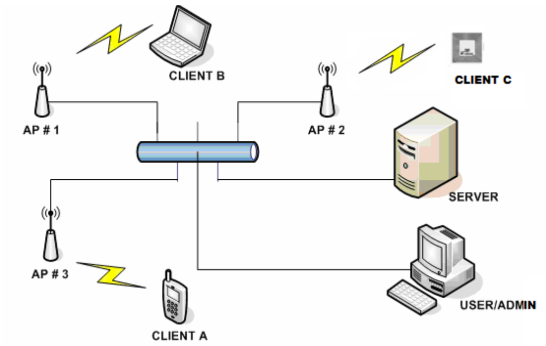

Figure 3: Overview of the Wi-Fi-Based Location Tracking System

The Wi-Fi clients are the targets for locating and tracking. The Data server collects signal strength information of the clients from the APs and provides network connections. The Data Server then calculates the position of target devices out of the received signal strength information using a location algorithm. An addressing mechanism is introduced to give each device a unique ID; therefore the Wi-Fi-based location tracking system is able to locate and track multiple clients simultaneously.

2. Locating Techniques

The accuracy of any location system is largely based on the location technique(s) deployed. All location techniques make use of the fact that certain quantities measurable in wireless networks vary with respect to the physical location where the measurement is done. The approaches of locating techniques make use of the following: Angle of Arrival (AoA) of the signal to multi-element directional antennas placed at the base station see Figure4; Time of Arrival (ToA) by knowing the time that a signal arrives, the distance between emitter (Tx) and receiver can be retrieved depicted as shown in Figure 5.

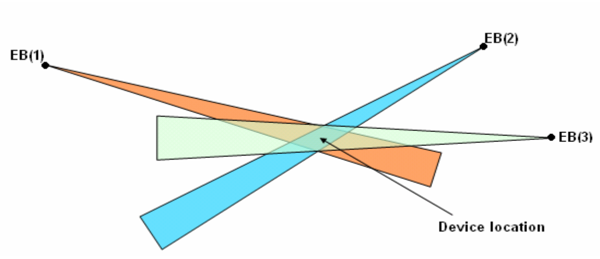

Figure 4: Wireless client location using Angle of Arrival

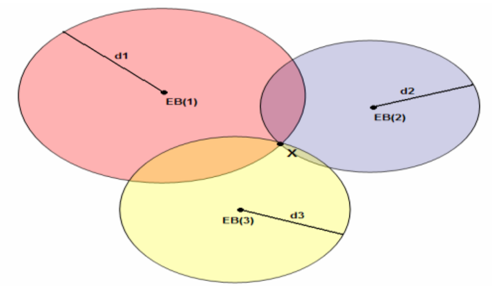

Figure 5: Wireless client location using Time of Arrival

Though, the possibilities of the above are described by a circumference with radius d_i for each base station and the intersection among all the circumferences (X) stands as the client's location [5], but the major disadvantage of AoA is its need of a clear line of sight. Multipath and reflection effects degrade the system accuracy, and make AoA not suitable for applications deployed in urban or indoor scenarios [6]. Another technique is the Time Difference of Arrival (TDoA), using Wi-Fi, this means that the client sends out a time stamped signal, which is received by the access points. Knowing the time difference, the distance between the AP and the client can be calculated. In a system with at least three visible access points, it becomes possible to estimate the location of the client as shown in Figure 6.

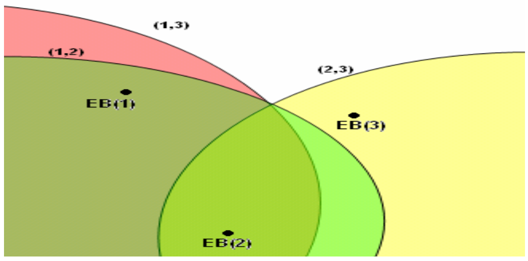

Figure 6: Wireless client location using Time Difference of Arrival

TDoA differs from ToA by using relative time values, where ToA uses absolute time values. More base stations can be used in the system improving TDoA accuracy, since more hyperbolas are also used. When a location request is made, new measurements take place and are compared with the ones collected during the calibration phase. The way the data is compared and the location is calculated is the core of the RF fingerprinting technique. Several methods exist like deterministic models (example: Euclidian distance), probabilistic models (example: find the likelihood of a device being at a given point) or other type of models where a simple mathematical approach is not enough (example: neural networks, vector machines, etc.). Each floor or building is defined as being distinct to others in terms of RF signatures. Moreover each location in each building must be unique so that the location pattern can give accurate results. It is a technique based on a software solution, when most of the time the RSSI measurements are enough to provide accurate results.

3. Measurements Collection and Location Computation

The server for the proposed location system is divided into three major sub-systems: the sub-system (micro-location with the objective of gathering measurements using RF fingerprinting for pinpointing user location); the second sub-system (location algorithm with the analysis of the received measurements from the micro-location subsystem) and the third sub-system is the web application that provides the user with an interface for displaying determined location of clients. These sub-systems are illustrated in Figure 7.

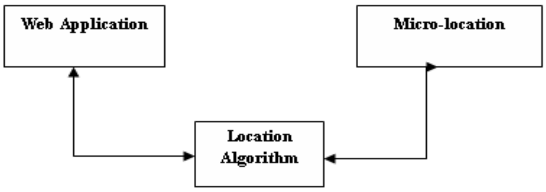

Figure 7: Sub-systems of the Server

The locations are identified as spatial coordinates (x, y). A third coordinate (z) could be included to indicate different floor levels. Typically, the more the number of RSSI measurements taken at the different locations, the higher the accuracy of the system. At each point, the RSSI measurement from each access point is measured. That is, for *n* number of access points, the signal strength vector is given as: $R_i = (a_{i1}, a_{i2}, \ldots, a_{in})$

Where ***i*** is the point of location and $\boldsymbol{a_{ij}}$ represents the RSSI measurement of point *i* from access point *j*. However, signal strength values vary according to the device orientation. This becomes especially problematic for devices that have Omni-directional antennas (such as PDAs, laptops, etc.). To minimize this effect on system performance, measurements were taken in all directions of the laptop and an average was recorded. The purpose of calibration is for comparison. This implies that when a request for location is received by the system, it retrieves signal strength values for the present request, and compares them with the calibration data. Artificial neural networks have the ability to learn with a defined data set [7, 9]. The data collected during the calibration phase is used to train the ANN, and after this training, the ANN can calculate wireless client location. The ANN of choice is the Multi Layer Perceptron (MLP) because of their ability to classify data patterns and also to approximate mathematical expressions efficiently.

The inputs for the ANN are the signal strength measurements taken in the calibration phase. The Fast Artificial Neural Network library (FANN) was use as this is a free open source neural network library, which implements multilayer artificial neural networks in C language that can support both fully connected and sparsely connected networks [8, 9].. The ANN implemented in this research work consists of one input layer, ten hidden layers and one output layer. The input layer consists of four (4) neurons representing the RSSI values from the four access points. The output layer consists of two (2) neurons signifying the location coordinates (x, y). Based on tests carried out with the ANN, the input values were normalized to values between -1 and 1 and this can be expressed as given in the equation below:

$$R_{norm} = \frac{2(R - R_{max})}{R_{max} - R_{min}} + 1$$

Python script was used to speed up the telnet process and collection of the RSSI values. It performs its function in three (3) basic steps which involves making a connection to the MySQL database to retrieve the Internet Protocol (IP) addresses of the access points. This process is looped to enable the access points to be polled individually and in turn. The IP addresses of the access points stored in a database, rather than being hard coded in the script, which allows the script to be scalable to accommodate more access points for the location system. The sub-process initiates the Telnet sessions to the access points. It is also concerned with retrieving the media access control (MAC) address of the device to be located from the request table of the database that a connection was previously made to. The script then sends commands required to retrieve the RSSI values of the required MAC address to the open Telnet session. Five (5) readings were taken for the same MAC address from each access point, and an average taken to reduce errors in calculation. Because of the normalized values input to the ANN, this sub-process also performs calculations for normalizing the retrieved RSSI values and stores the result in a text file and finally the sub-process initiates the execution of the ANN program. The RSSI values stored in the text file from the previous sub-process are read by the C program as input to the ANN created during the training phase.

4. Result and Achievement

As expected, these RSS values were not constant in all directions, and varied up to about -4dBm. This is mainly due to device orientation and also to the nature of the indoor radio propagation channel. An average of four values taken was computed to make up the calibration data.

The tables of values of the results are presented below:

Table1: Number of training data versus Mean square error

No of training data	MSE (m)
45	0.005432
50	0.003004
56	0.000858

Table2: Real Outputs against Calculated Output from Artificial Neural Network (x coordinate)

Real Output2	Calculated Output2
0.222222	0.251288
0.296296	0.299025
0.333333	0.324376
0.000000	0.043135
0.888889	0.907149
0.925926	0.953372
1.000000	0.964981
0.222222	0.266416
0.277778	0.247636
0.296296	0.259894
0.333333	0.277491
0.222222	0.238971
0.296296	0.277491
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Table3: Real Outputs against Calculated Output from Artificial Neural Network (y coordinate)

Real Output1	Calculated Output1
0.027778	0.047208
0.027778	0.044594
0.027778	0.044796
0.043210	0.058529
0.043210	0.087227
0.043210	0.037853
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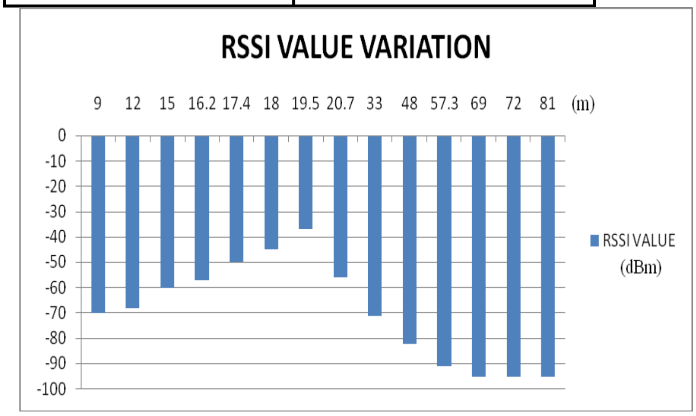

Figure 8: Access point1's received signal strength variation along length of building

Received signal strength collected by clients from wireless access points are measured in dBm units. These values ranged from -37dBm to -94dBm. Higher values are indicated when a client is close to the access point. Location points that did not receive signal from certain access points were assigned a minimum RSSI value of -95dBm.

Artificial Neural Network

Two different sets of data were collected for use with the ANN. One set was for training the network, and the other was for its testing.

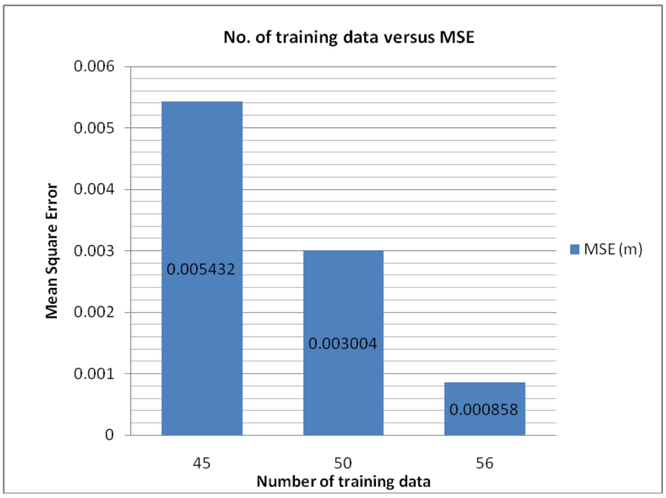

Figure 9: Chart showing comparison between Number of training data an MSE

The figure 9 above shows that as the training data increased, the mean square error (MSE) of the network reduced. The training data was then increased to about fifty five (55) training sets and the network showed good performance.

After the network was trained, test data were then fed into it to determine its accuracy. The two figures below, Figure 10 and Figure 11, show the comparison between the real outputs and the calculated outputs from the ANN. As can be seen, the ANN adapted to the problem efficiently.

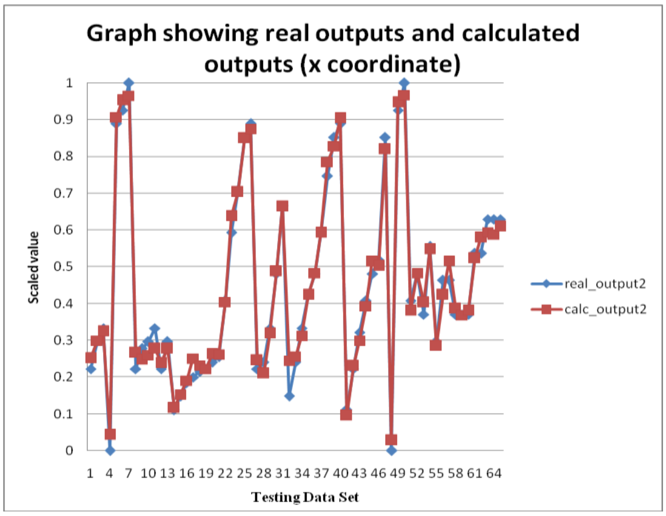

Figure 10: Graph comparing real and calculated output (x coordinate)

The horizontal axis represents the testing data set (which comprises of RSSI values and corresponding location outputs). Sixty five (65) different testing data sets were used in testing the data with the largest variation in the x coordinate being 0.096505 which is approximately 8m. The average error of output for the x coordinate is 0.022949 which is about 1.86m.

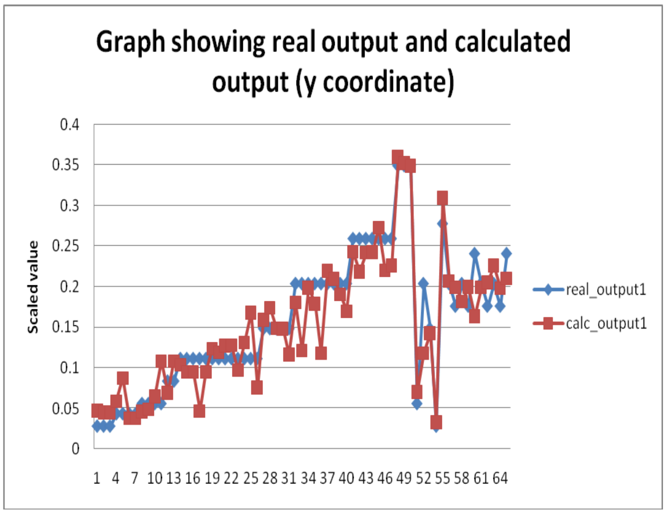

Figure 11: Graph comparing real and calculated output (y coordinate)

The largest variation between the calculated and real output for the y coordinate is 0.085602 which approximates to about 7m.

The average error for the y coordinate was found to be 0.021784 which is about 1.76m.

5. Conclusion

From the test results shown, it is evident that the developed system has met up with the specifications of accuracy and speed. Minimal cost is also incurred since the operation of the developed location system is independent of any specialized hardware device. Furthermore, flexibility has been achieved through the use of artificial neural network as the technique for location algorithm. The idea behind an indoor location system is its capability of providing accuracy while being simple to use. The location system developed can be easily deployed in existing WLAN with minimal cost and difficulty, without making changes to the network structure or even the client devices. The system's performance is not degraded by minimal environmental changes in indoor location, and multi-path and small scale fading effects encountered in indoor radio propagation. The 'location algorithm' is responsible for computing location coordinates based on received values, and the 'web application' interacts with the end user to provide location information.

6. REFERENCES

[1] Yibo Chen and Rong Luo: "*Design and Implementation of a Wi-Fi-based Local Locating System*", IEEE, 2007

[2] MJ.Callaghan, P.Gormley, M.McBride, J.Harkin and TM.McGinnity: "*Internal Location Based Services using Wireless Sensor Networks and RFID Technology",* IJCSNS International Journal of Computer Science and Network Security, VOL.6 No.4, April 2006, pp 108-109

[3] Ni,Lionel M., Liu,Yunhao, "*LANDMARC: Indoor Location Sensing Using Active RFID*", Wireless Networks, 10, 6, Nov. 2004, pp. 701-710.

[4] "*Microsoft Encarta 2009*" Microsoft Corporation.

[5] Pedro Miguel, Ferreira Claro: "*Local Positioning System Based on Wi-Fi Networks"*, University of Aveiro, Departamento de Electrónica e Telecomunicações, 2006, pp. 20, 32-35, 51

[6] "*Emerging Technologies in Wireless LANs: Theory, Design, and Deployment"*, Edited by Benny Bing, Ekahau Corporations, 2007.

[7] M.T. Hagan et al.: "*Neural Network Design*". Boston, EUA: PWS, 1996.

[8] "*Fast Artificial Neural Network"* < http://leenissen.dk/fann/>. Accessed February 14, 2009.

[9] Ibikunle F.: "Artificial Neural Networks: Module 2", unpublished B.Eng Lecture Notes, Covenant University, Ogun state, Nigeria, 2009.