2013

RSSI Based Indoor Localization for Smartphone Using Fixed and Mobile Wireless Node

Md O. Gani
Marquette University, md.gani@marquette.edu

Casey O'Brien
Marquette University, casey.obrien@marquette.edu

Sheikh Iqbal Ahamed
Marquette University, sheikh.ahamed@marquette.edu

Roger O. Smith
University of Wisconsin - Milwaukee

2013 IEEE 37th Annual Computer Software and Applications Conference, (July 22-26, 2013): 110-117. DOI.

RSSI Based Indoor Localization for Smartphone Using Fixed and Mobile Wireless Node

Md. Osman Gani
Department of Mathematics, Marquette University, Milwaukee, WI
Casey O'Brien
Marquette University, Milwaukee, WI
Sheikh I. Ahamed
Department of Mathematics, Marquette University, Milwaukee, WI
Roger O. Smith
Rehabilitation Research Design and Disability Center, University of Wisconsin-Milwaukee, Milwaukee, WI

Abstract:
Nowadays with the dispersion of wireless networks, smartphones and diverse related services, different localization techniques have been developed. Global Positioning System (GPS) has a high rate of accuracy for outdoor localization but the signal is not available inside of buildings. Also other existing methods for indoor localization have low accuracy. In addition, they use fixed infrastructure support. In this paper, we present a novel system for indoor localization, which also works well outside. We have developed a mathematical model for estimating location (distance and direction) of a mobile device using wireless technology. Our experimental results on Smartphones (Android and iOS) show good accuracy (an error less than 2.5 meters). We have also used our developed system in asset tracking and complex activity recognition.

SECTION I. Introduction
Man invented several methods and tools to identify their location a long time ago. Nowadays localization plays a very important role. Various location based services (LBS) has been developed using global positioning system (GPS) for outdoor environment. There are lots of applications where localization is used extensively such as navigation, map generation, complex activity recognition, patient identification, location and tracking in hospitals, child tracking, disaster management, monitoring firefighters, indoor and outdoor navigation for humans or mobile robots, inventory control in factories, anomaly detection, customer interest observation in supermarkets, visitors interest observation in exhibitions, and smart houses [1] [2] [3] [4] [5]. These applications of localization help to solve and improve a variety of real-life problems.

GPS has a high rate of accuracy for outdoor localization. But it is not viable to use GPS indoors or to use wireless sensor networks (WSNs) because it is expensive in terms of energy and cost. Also the signal is not available inside the building. Besides GPS, most of the other existing methods use infrastructure to estimate location both indoors and outdoors, so these methods require additional cost for the infrastructure. As infrastructure is stationary in terms of long range user mobility, it is not possible to identify the location of the user accurately and sometimes they leave the service region. Some methods are adaptive and others need training each time there is a change in environment. Some of the approaches require additional setup time to start working. So to improve accuracy it takes time to recalibrate the system every time there is a change in environment.

Nowadays there is a huge growth in the number of Smartphone users. Total shipments of Smartphones in 2011 were 491.4 million with annual growth 61.3% percent from 2010 [6]. Every Smartphone is equipped with various wireless adapters and offers a variety of useful sensors such as Accelerometer, Gyroscope, Orientation sensor, Magnetometer, Barometer, GPS, Wi-Fi, and NFC. Use of a Smartphone based system eliminates cost of additional devices and sensors.

In order to solve existing problems such as improving accuracy, eliminating infrastructure, reducing cost and setup time, and adding mobility we worked on developing a system for localization. We developed a mathematical model for estimating location (distance and direction) of a mobile device indoors and outdoors using Wi-Fi. We used our developed model to build a localization system for Smartphones (Android/iPhone). We also implemented another approach called the fingerprint approach, to identify Smartphone location using multiple mobile and fixed wireless routers.

In this paper, we present a novel approach to determine the location of a mobile node using mobile and fixed wireless routers. Our proposed approach has the following contributions:

- Established a new system to model the localization with RSSI
- Smartphone based system which is cost effective and easy to use.

- Improved localization accuracy in a ubiquitous fashion
- System is able to protect user privacy
- Comparison of system accuracy with mobile and fixed wireless node (router)

The rest of the paper is organized as follows. Section II states the existing approaches and techniques of localization. We describe the details of our approach in Section III. Evaluation, limitations, and possible improvements are discussed in Section IV. Finally we conclude the paper with future work in section V.

SECTION II. Related Works

There has been a lot of research works on indoor and outdoor localization using wireless technology such as Wi-Fi (Wireless Fidelity, IEEE 802.11), ZigBee (IEEE 802.15.4), and RFID (Radio Frequency Identification) [2]–[3][4][5][6][7][8][9][10][11][12][13][14][15][16][17][18][19][20][21][22][23][24][25][26][27][28]. Currently, there are several methods for estimating positioning. The three types of measurements mainly used a) Angle of Arrival (AOA) b) Time of Arrival (TOA) and Time Difference of Arrival (TDOA) and c) Received Signal Strength Indicators (RSSI). Each of these parameters has some advantages and disadvantages. In contrast with AOA, TOA/TDOA measuring the RSSI value is very simple and also available in all of the existing wireless systems. That is why RSSI based methods are preferable and easy to implement.

We can consider RSSI as a function of distance from the source even though it changes for various reasons such as propagation losses, complex indoor layout, depending on the orientation of the source and receiver, line of sight (LOS) requirement and environmental changes. The key complexity is that wireless signals in an indoor environment suffer from interference and attenuation from multi-path fading, reflection, channel fading, deflection, and diffraction. Due to the unpredictable behavior of signal, finding location with a low error rate is a great challenge.

In the last few years, researchers proposed, simulated and implemented several algorithms and techniques on localization using RSSI values and propagation time of wireless devices. Some of these are a) Log distance path loss model, b) Trilateration, c) Multilateration, d) Fingerprint method, e) Centroid algorithm, f) Weighted Centroid algorithm, g) Maximum likelihood estimation (MLE), h) K-nearest neighbor method, i) Kalman filter, j) Particle filtering algorithm and k) Gaussian model. Almost all of the method used the RSSI value, a number of reference or anchor nodes (Access Point or APs), and a fingerprint map or RSSI database for estimating location. We tabulated summary of different localization approaches in Table I.

TABLE I: Comparison Of Different Approaches Of Location

Work	Area	Location	Algorithm	Parameters	Application	Error	Experiment
Fink et al. [1]	WSN	Indoor	Path loss model Kalman Filter	RSSI Beacon node	Indoor positioning	4.85m	Real time
Blumrose n et al. [2]	WSN	Indoor	MAP criterion	RSSI Anchor node Close proximity Line of Sight (LOS)	Tracking moving object in close proximity for medical application	Mean 0.7cm Std Dev 4cm	Real time
Zhang et al. [3]	Zig Bee	Not specified	Gaussian model Log path loss model Optimization algorithm	RSSI Reference Node	Tracking multiple mobile robot	3.38m to 5.1m	Simulation in Mat lab
Huang et al. [4]	Zig Bee	Not specified	Log path loss model Antenna polarization	RSSI Reference Node Accelerometer	Location identification	1.5m	Real time
Zhang et al. [5]	Zig Bee	Outdoor	Gaussian model Trilateration	RSSI Beacon node	Localization	**1** to 5 m	Real time
Ibrahim et al. [7]	GSM	Not specified	Probabilistic fingerprint localization technique	RSSI Cell information database	GSM positioning system	Improved accuracy 23.8% and 86.4%	Real time
Ching et al. [8]	WLAN	Indoor	Radio Map	RSSI Reference Node	Position detection	Accuracy: 32%-47% to find exact room	Real time
Heredia et al. [9]	WLAN	Indoor	Hidden Markov Model (HMM) Viterbi algorithm	RSSI Reference APs	People location system	50%	Real time
Lee et al. [10]	WiMAX	Outdoor	Matrix Pencil for AOA	AOA RSSI	2D multi-user location system	<10m in 1Km range	Simulation in WiBro
Feng et al. [11]	WSN	Indoor Line of sight	Adaptive Neural-Fuzzy Inference System	RSSI 3 Beacons	Distance measure	2m mean	Real time
Teo et al. [12]	WSN	Indoor	Hop count based localization	RSSI	Distance measure	NA	Real time
Graefenst emn et al. [13]	Zig Bee	Outdoor	Probability torus Sequence based localization	RSSI N Beacon node	Path driven by a robot in a map	0.95m to 2.17m	Real time
Rolfe et al. [14]	RFID	Indoor	K-Nearest Neighbors ANN (MLP)	RSSI Beacon Node	Indoor localization	83%	Real time

Zhong et al. [15]	Zig Bee	Indoor	Min-Max	RSSI Anchor Node	Monitoring firefighters	5m mean	Real time
Salama et al.[16]	RFID	Outdoor	Trilateral Path loss model	RSSI Beacons	Track and monitor object in university area	6.7m	Simulation in Mat lab
Wong et al. [17]	GPS Bluetooth	Outdoor	Approximation of distance from RSSI [$Y = -13.3 \ln(x) — 47$]	GPS RSSI	Child tracking	Not specified	Real time
Chen et al. [18]	WSN	Not specified	Weighted Centroid algorithm	RSSI Beacon node	Target localization and tracking	RMSE less than 3m	Simulation
Chang et al. [19]	WLAN	Indoor	Dominant AP's algorithm	RSSI Reference Node	Location Based Services	Mean 3m	Real time
Tang et al. [20]	WSN	Not specified	Log distance path loss model Lateration estimation	RSSI Reference Node	Anomaly Detection for WSN	Not specified	Simulation
Widyawa n et al. [21]	WLAN	Indoor	K-nearest neighbor Particle filter Map filtering	RSSI Anchor Node	WLAN	Mean 1.98m Std. Dev. 1.39m	Real time
Ahn et al. [22]	WSN	Indoor	Log distance path loss model Weighted Centroid	RSSI Anchor Node	ZigBee	Not specified	Real time
Fink et al. [23]	WSN	Indoor	Antenna Diversity and Plausibility Filter	RSSI Reference Node	WSN Safety application in Industrial Automation	1 to 2.56m	Real time
Lee et al. [24]	RFID	Not specified	Unscented Kalman and Particle Filter	RSSI Reference Node	Tracking object	2.2m for PF and 7.19m for UKF	Real time
Jinpeng et al.[25]	wsN	Under ground	Weighted minimum variance Centroid MLE	RSSI Reference Node	ZigBee Locate underground miners, vehicles and detect temperature	Location 20.5% distance 33.8%	Real time
Chen et al. [26]	Zig Bee	Outdoor	Piecewise linear path loss model Min-Max	RSSI Static Node	Park lighting control Child tracking	RMS 3.5228	Real time
Komatsu et al.[27]	WSN	Not specified	RSSI formation control	RSSI Beacon node	Control mobile robot	Not specified	Simulation
Lau et al. [28]	RFID	Indoor Outdoor	Enhancement algorithm	RSSI Reference Node	Tracking user location	Mean 2.8m	Real time

SECTION III. Our Approach

A. Localization of Mobile Wi-Fi Node with Smartphone

In this approach we used the RSSI value of a wireless network as the parameter to estimate location (distance and direction) of a mobile wireless node using a Smartphone (Fig. 1). At first we collected RSSI values for both indoor and outdoor environments. Then we used a low pass filtering method to eliminate noise in RS SI which is caused by various environmental factors. This filtering enhances the usability and acceptability of the RSSI value as a parameter to estimate distance and direction of a mobile node from a Smartphone. In our experiment we used Roving Networks WiFly RN-131GSX as a mobile Wi-Fi router.

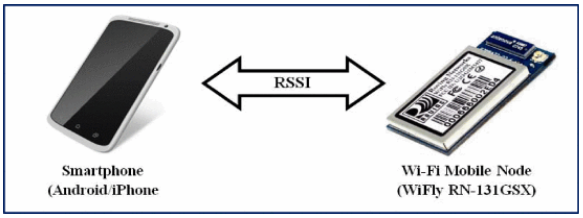

Figure 1. Localization of mobile Wi-Fi node (router) with Smartphone.

We collected RSSI values for both indoor and outdoor environments using Android and iPhone. These measurements were taken for distances of 10 feet to 80 feet between the Smartphone and mobile Wi-Fi node. We stored the pair (distance, RSSI) for all the distinct locations with 2 feet intervals. We also computed direction, θ which is direction from the true north for each collected RSSI value. We used the accelerometer and magnetometer sensors of the Smartphone to compute direction from true north. Then we used the following mathematical model for predicting distance and direction of the mobile Wi-Fi node.

1) Mathematical Model

We used result from a separate experiment (RSSI value and orientation of smartphone and wireless node) to build the mathematical model. From the experimental result, we found that RSSI value varies with the orientation of mobile device and Wi-Fi node. To normalize the orientation effect we collected RSSI value with the rotation of smartphone by 360 degree on the horizontal plane. Then we used mean value of the collected RSSI to compute the distance. We found that rotation of the smartphone reduces the orientation effect on the RSSI value. We also found RSSI value is strongest, when the smartphone orientation point towards the Wi-Fi node (Line of Sight). Based on this result, we computed direction as the angle from true north for which we get the strongest RSSI signal. The mathematical model to predict distance and direction i.e. location of mobile node is shown in Fig. 2. The overall approach is shown in Fig. 3.

- ***Direction***

$$rssi = \{rssi_0, rssi_1, rssi_2, \ldots, rssi_n\} \;,\; for\ 0 \le \theta \le 360$$

$$rssi_{\max} = \{rssi_j \mid rssi_j > \forall_{i, i \ne j} rssi_i\}$$

$$direction = \{\theta_i \mid rssi_{\max} = rssi_i,\ current\ direction\ is\ \theta_i\ from\ true\ north\}$$

- ***Distance***

$$(d, rssi_{mean})\ \ where\ \ rssi_{mean} = \frac{1}{n}\sum_{j=0}^{n} rssi_j \;,\; for\ 0 \le \theta \le 360$$

Figure 2. Mathematical Model.

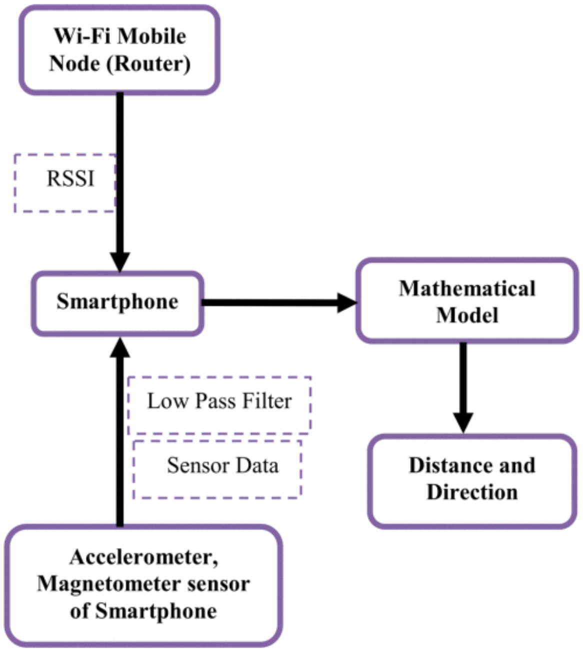

Figure 3. Overall Approach.

Here we used filtered accelerometer sensor and magnetometer sensor data to compute the heading. In the same time we collected RSSI from mobile node for each degree rotation. Then we used mathematical model to predict distance and direction of the mobile node from smartphone.

We used exponential regression using Nelder-Mead Simplex Search method [29] [30]. As RSSI values vary with vendors we collected 4 different sets of data and used 4 different regressions for indoor and outdoor environment with Android and iPhone. We show the regression for outdoor environment using Android in Fig. 4.

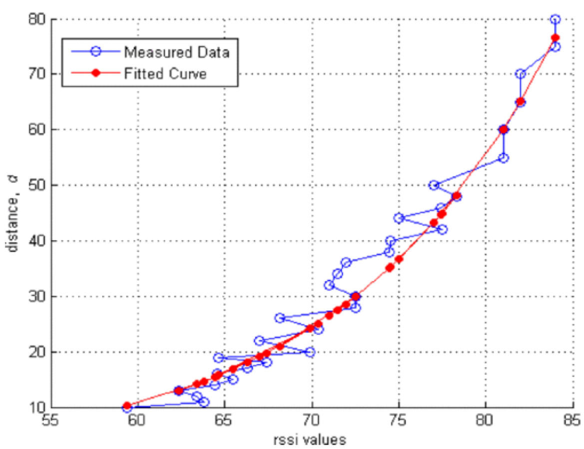

Figure 4. Exponential regression for outdoor on Android.

2) Result

The regression function is then used to estimate location. We developed a working prototype on the Smartphone (both Android and iPhone) using this model. Then we computed the accuracy of both the Android and iPhone systems for indoor and outdoor environments. The result is tabulated in Table II. We also developed a different tool for collecting data and computing location.

TABLE II: Accuracy Of The Developed System

System	Environment	Accuracy	Percentage
Android	Indoor	< 2.0 meters	85%
	Outdoor	. < 1.5 meters	90%
iPhone	Indoor	< 2.5 meters	80%
	Outdoor	< 1.8 meters	90%

B. Localization of Smartphone with Wi-Fi Routers

In this approach we tried to localize the user with a Smartphone within a single, open spaced room using the previously observed *RSSI*. We did the experiment in the UbiComp Lab, Marquette University. Here we imposed 6 points (12 grids) inside the room. Then we placed 3 WiFly RN-131GSX in different places. We also used the publicly available 3 MU Wireless routers for our experiment. The details of the experiment setup are shown in Fig. 5. The dimension of the UbiComp lab is 31.6 feet by 24.8 feet. We used 12 equally spaced grids in the experiment.

We collected RSSI vectors (1×3) for each of the six points for both WiFly routers and MU Wireless routers. We developed a tool in Android to collect data. Data collection frequency was 9–10 Hz. We collected 1000 samples for approximately 1.7 minutes. Then we generated histogram cumulative means for some of the points are shown in Fig. 8, Fig. 9 and Fig. 10. We can see in almost all of the cases (Fig. 8, Fig. 9 and Fig. 10) RSSI converges to the mean value around 300 samples. So we decided to collect around 300 samples during test phase. We created RSSI signature using mean value of collected RSSI samples.

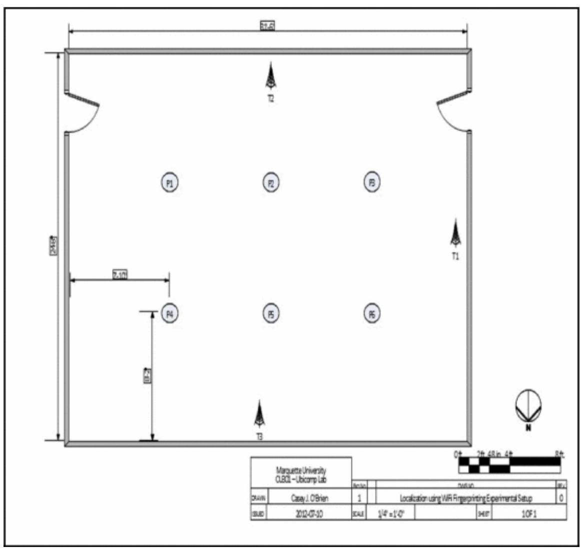

Figure 5. Floor Map of test bed at UbiComp Lab, Marquette University.

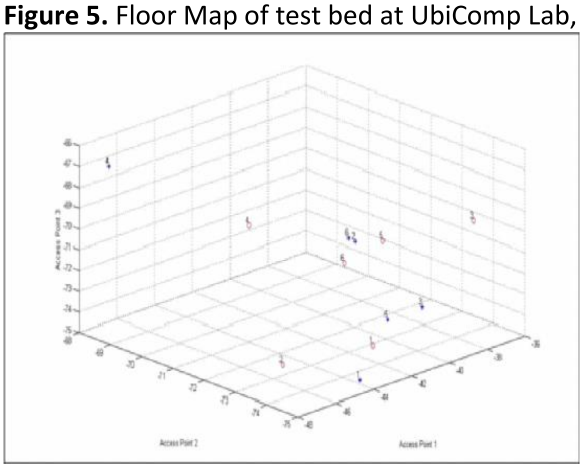

Figure 6. Observed RSSI signature of 6 points using 3 mobile (WiFly) routers for two different datasets.

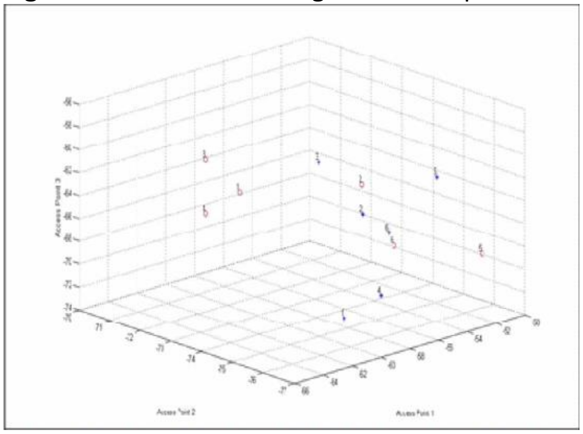

Figure 7. Observed RSSI signature of 6 points using 3 fixed (MU Wireless) routers for two different datasets.

We did the same experiment using 3 publicly available MU Wireless routers and generated the cumulative mean and a histogram. Also using the mean *RSSI* of collected samples, we created an *RSSI* signature. This signature will be compared to the observed *RSSI* vector during the test phase. The signature of 6 different points for both routers is shown in the Fig. 6 and Fig. 7. From the figures, we can see the difference (distance) between the signatures for different points. This property has been used for the prediction.

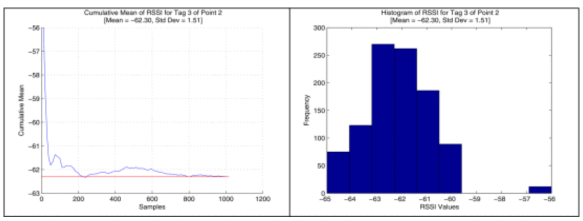

Figure 8. Histogram and Cumulative Mean of collected Samples at WiFly 3 of Point 2.

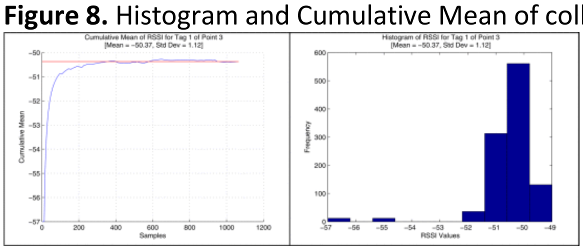

Figure 9. Histogram and Cumulative Mean of collected Samples at WiFly 1 of Point 3.

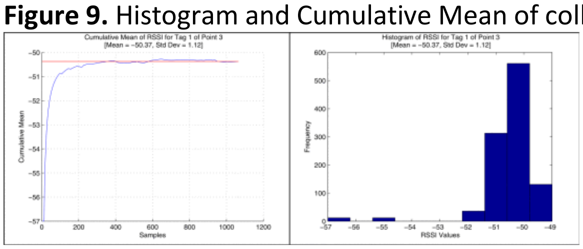

Figure 10. Histogram and Cumulative Mean of collected Samples at WiFly 3 of Point 6.

TABLE III: Accuracy Of The Developed System

Wireless Router	Location	Computed Location
WiFly RN- 131 GSX	Point 1	Point 1 (100%)
	Point 2	Point 1 (100%)
	Point 3	Point 1 (100%)
	Point 4	Point 4 (90%)

		Point 1 (10%)
	Point 5	Point 4 (70%)
		Point 6 (30%)
	Point 6	Point 6 (80%)
		Point 4 (20%)
MU Wireless	Point 1	Point 1 (70%)
		Point 5 (30%)
	Point 2	Point 3 (40%)
		Point 1 (30%)
		Point 5 (30%)
	Point 3	Point 3 (100%)
	Point 4	Point 4 (70%
		Point 6 (30%)
	Point 5	Point 5 (80%)
		Point 1 (20%)
	Point 6	Point 6 (80%)
		Point 5 (20%)

We used this observed *RSSI* signature to predict location during the test phase. We developed a tool in Android to predict location using observed *RSSI* signature. We predicted 6 different points using both WiFly and MU Wireless routers. The result is tabulated in Table III.

SECTION IV. Discussion

The goal of this research is to design and develop an infrastructure-less intelligent ubiquitous system which is able to detect the location of the user both indoors and outdoors with a high accuracy using wireless technology. For localization of a mobile node with a Smartphone, we achieved less than 2 meters accuracy with an Android and less than 2.5 meters accuracy with an iPhone for both indoor and outdoor. We achieved a good accuracy without using infrastructure. From Table I, we see most of the approaches use infrastructure to achieve this accuracy. It reduces the cost. Also it can be used in both indoors and outdoors. We did the experiment in real time to test the performance of the system. We also applied our localization approach. We used the first approach to design and develop asset tracking system (Android/iPhone). We used the second approach in activity recognition system. To localize a Smartphone with a wireless router we achieved 80% accuracy for 5 out of 6 different locations with MU Wireless routers. We achieved low accuracy (30% to 40%) for mobile nodes or WiFly routers.

We evaluated our designed system by implementation in two different scenarios. We built an asset tracking system for smartphones using the first approach. Here the mobile node (WiFly) is integrated with the asset to be tracked. Then we developed two separate applications in Android and iOS for the smartphone to track the distance and direction of the mobile node. The application can find the location of the mobile node, fire alarm in the mobile node. Also user can activate a leash function to keep track of the distance of the mobile node. Once the mobile node is out of preset perimeter, the application fires an alarm in the smartphone. We used the open-source electronics prototyping platform “Arduino” in our developed system.

We also used our localization technique for Complex Activity Recognition (sleeping, eating, watching TV, washing dish, taking shower etc.). We implemented our system in an apartment to find the location (bed room, kitchen, dining, living room, lawn etc.) of the user. Using a Smartphone we are able to detect the time, location and weather easily. We also considered other parameters that influence human activity to create a vector of attributes. Then we trained our system by collecting these parameters. Later we calculate distance between the trained parameterized vector and current vector to determine different kind of activities.

Though we achieved good accuracy in the first experiment we got less accuracy in the second experiment. We achieved better accuracy with fixed a wireless router than mobile wireless router. We think that a battery powered mobile wireless router is more vulnerable to the environment which influences RSSI by a large factor. We also think that modeling RSSI with orientation and environmental changes will be helpful for better prediction. Also automatic map generation using Smartphones will be helpful for better navigation and take low setup time.

SECTION V. Conclusion

We achieved good accuracy for the first approach without using any kind of infrastructure. Also use of kinematic sensors of smartphone with the help of this approach can be used to develop indoor navigation system. We plan to work on the second approach to improve the accuracy. Inclusion of publicly available parameters (like cellular network information, wireless devices) in the system which is available within the range can accelerate accuracy of the future system. We plan to create an RSSI map database considering orientation and environmental changes which will be helpful for the second approach.

References

1. Fink, A.; Beikirch, H.; Voss, M.; Schröder, C.;, "RSSI-based indoor positioning using diversity and Inertial Navigation," Indoor Positioning and Indoor Navigation (IPIN), 2010 International Conference on, vol., no., pp.1-7, 15-17 Sept. 2010

2. Blumrosen, Gaddi; Hod, Bracha; Anker, Tal; Dolev, Danny; Rubinsky, Boris;, "Continuous Close-Proximity RSSI-Based Tracking in Wireless Sensor Networks," Body Sensor Networks (BSN), 2010 International Conference on, vol., no., pp.234-239, 7-9 June 2010

3. Qingxin Zhang; Qinglong Di; Guangyan Xu; Xiaoyan Qiu;, "A RSSI based localization algorithm for multiple mobile robots," Computer, Mechatronics, Control and Electronic Engineering (CMCE), 2010 International Conference on, vol.4, no., pp.190-193, 24-26 Aug. 2010

4. Xu Huang;, "Antenna Polarization as Complementarities on RSSI Based Location Identification," Wireless Pervasive Computing, 2009. ISWPC 2009. 4th International Symposium on, vol., no., pp.1-5, 11-13 Feb. 2009

5. Yunchun Zhang; Zhiyi Fang; Ruixue Li; Wenpeng Hu;, "The Design and Implementation of a RSSI-Based Localization System," Wireless Communications, Networking and Mobile Computing, 2009. WiCom '09. 5th International Conference on, vol., no., pp.1-4, 24-26 Sept. 2009

6. IDC Worldwide Mobile Phone Tracker, February 6, 2012

7. Ibrahim, M.; Youssef, M.;, "CellSense: A Probabilistic RSSIBased GSM Positioning System," GLOBECOM 2010, 2010 IEEE Global Telecommunications Conference, vol., no., pp.1-5, 6-10 Dec. 2010

8. Ching, W.; Rue Jing Teh; Binghao Li; Rizos, C.;, "Uniwide WiFi based positioning system," Technology and Society (ISTAS), 2010 IEEE International Symposium on, vol., no., pp.180-189, 7-9 June 2010

9. Heredia, B.; Ocaa, M.; Bergasa, L.M.; Sotelo, M.A.; Revenga, P.; Flores, R.; Barea, R.; Lopez, E.;, "People Location System based on WiFi Signal Measure," Intelligent Signal Processing, 2007. WISP 2007. IEEE International Symposium on, vol., no., pp.1-6, 3-5 Oct. 2007

10. Jeongsu Lee; Kim, N.Y.; Sujin Kim; Joonhyuk Kang; Youngok Kim;, "Joint AOA/RSSI based multi-user location system for military mobile base-station," Military Communications Conference, 2008. MILCOM 2008. IEEE, vol., no., pp.1-5, 16-19 Nov. 2008

11. Xiufang Feng; Zhanqiang Gao; Mian Yang; Shibo Xiong;, "Fuzzy distance measuring based on RSSI in Wireless Sensor Network," Intelligent System and Knowledge Engineering, 2008. ISKE 2008. 3rd International Conference on, vol.1, no., pp.395-400, 17-19 Nov. 2008

12. Tet Sen Teo; Chee Siang Lim; Joo Ghee Lim; Kirn Loon Chee; Sivaprasad, P.K.;, "Feasibility stud of RSSI in improving hop-count based localization," Communications Systems, 2004. ICCS 2004. The Ninth International Conference on, vol., no., pp.621-625, 7-7 Sept. 2004
13. Graefenstein, J.; Bouzouraa, M.E.;, "Robust method for outdoor localization of a mobile robot using received signal strength in low power wireless networks," Robotics and Automation, 2008. ICRA 2008. IEEE International Conference on, vol., no., pp.33-38, 19-23 May 2008
14. Rolfe, B.F.; Ekanayake, S.W.; Pathirana, P.N.; Palaniswami, M.;, "Localization with orientation using RSSI measurements: RF map based approach," Intelligent Sensors, Sensor Networks and Information, 2007. ISSNIP 2007. 3rd International Conference on, vol., no., pp.311-316, 3-6 Dec. 2007
15. Chen Zhong; Eliasson, J.; Mäkitaavola, H.; Fan Zhang;, "A Cluster-Based Localization Method Using RSSI for Heterogeneous Wireless Sensor Networks," Wireless Communications Networking and Mobile Computing (WiCOM), 2010 6th International Conference on, vol., no., pp.1-6, 23-25 Sept. 2010
16. Salama, A.M.A.; Mahmoud, F.I.;, "Using RFID technology in finding position and tracking based on RSSI," Advances in Computational Tools for Engineering Applications, 2009. ACTEA '09. International Conference on, vol., no., pp.532-536, 15-17 July 2009
17. Kok Sun Wong; Wei Lun Ng; Jin Hui Chong; Chee Kyun Ng; Sali, A.; Noordin, N.K.;, "GPS based child care system using RSSI technique," Communications (MICC), 2009 IEEE 9th Malaysia International Conference on, vol., no., pp.899-904, 15-17 Dec. 2009
18. Yanjun Chen; Quan Pan; Yan Liang; Zhentao Hu;, "AWCL: Adaptive weighted centroid target localization algorithm based on RSSI in WSN," Computer Science and Information Technology (ICCSIT), 2010 3rd IEEE International Conference on, vol.9, no., pp.331-336, 9-11 July 2010
19. Chang-Beom Lim; Sung-Hun Kang; Hyun-Hun Cho; Sin-Woo Park; Joon-Goo Park;, "An Enhanced Indoor Localization Algorithm Based on IEEE 802.11 WLAN Using RSSI and Multiple Parameters," Systems and Networks Communications (ICSNC), 2010 Fifth International Conference on, vol., no., pp.238-242, 22-27 Aug. 2010
20. Jiayu Tang; Pingzhi Fan;, "A RSSI-Based Cooperative Anomaly Detection Scheme for Wireless Sensor Networks," Wireless Communications, Networking and Mobile Computing, 2007. WiCom 2007. International Conference on, vol., no., pp.2783-2786, 21-25 Sept. 2007
21. Widyawan; Klepal, M.; Pesch, D.;, "Influence of Predicted and Measured Fingerprint on the Accuracy of RSSI-based Indoor Location Systems," Positioning, Navigation and Communication, 2007. WPNC '07. 4th Workshop on, vol., no., pp.145-151, 22-22 March 2007
22. Hyochang Ahn; Sang-Burm Rhee;, "Simulation of a RSSIBased Indoor Localization System Using Wireless Sensor Network," Ubiquitous Information Technologies and Applications (CUTE), 2010 Proceedings of the 5th International Conference on, vol., no., pp.1-4, 16-18 Dec. 2010
23. Fink, A.; Beikirch, H.; Vos, M.;, "RSSI-based localization in functional safety applications of industrial automation," Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications, 2009. IDAACS 2009. IEEE International Workshop on, vol., no., pp.629-634, 21-23 Sept. 2009
24. Kung-Chung Lee; Oka, A.; Pollakis, E.; Lampe, L.;, "A comparison between Unscented Kalman Filtering and particle filtering for RSSI-based tracking," Positioning Navigation and Communication (WPNC), 2010 7th Workshop on, vol., no., pp.157-163, 11-12 March 2010
25. Tian Jinpeng; Shi Huichang; Guo Wenliang; Zhou Yifei;, "A RSSI-Based Location System in Coal Mine," Microwave Conference, 2008 China-Japan Joint, vol., no., pp.167-171, 10-12 Sept. 2008
26. Jia Chen; Xiao-jun Wu; Feng Ye; Ping Song; Jian-wei Liu;, "Improved RSSI-based localization algorithm for park lighting control and child location tracking," Information and Automation, 2009. ICIA '09. International Conference on, vol., no., pp.1526-1531, 22-24 June 2009
27. Komatsu, T.; Ohkubo, T.; Kobayashi, K.; Watanabe, K.; Kurihara, Y.;, "A study of RSSI-based formation control algorithm for multiple mobile robots," SICE Annual Conference 2010, Proceedings of, vol., no., pp.1127-1130, 18-21 Aug. 2010

28. Erin-Ee-Lin Lau; Wan-Young Chung;, "Enhanced RSSIBased Real-Time User Location Tracking System for Indoor and Outdoor Environments," Convergence Information Technology, 2007. International Conference on, vol., no., pp.1213-1218, 21-23 Nov. 2007
29. J. A. Nelder and R. Mead, A Simplex Method for Function Minimization, Computer Journal (1965), 308{313}.
30. Lagarias, J.C., J. A. Reeds, M. H. Wright, and P. E. Wright, "Convergence Properties of the Nelder-Mead Simplex Method in Low Dimensions," SIAM Journal of Optimization, Vol. 9 Number 1, pp. 112-147, 1998.