Enhancing Wi-Fi Signal Strength of a Dynamic Heterogeneous System Using a Mobile Robot Provider

Esther Rolf[1], Matt Whitlock[2], Byung-Cheol Min[3], and Eric T. Matson[3]

[1] Princeton University, Princeton, NJ, USA
[2] The University of Alabama, Tuscaloosa, AL, USA
[3] Machine-to-Machine (M2M) Lab, Department of Computer and Information Technology, Purdue University, West Lafayette, IN 47907 USA
`erolf@princeton.edu`, `mswhitlock@crimson.ua.edu`, `{minb,ematson}@purdue.edu`

Abstract. Heterogeneous networks of humans, robots, and agents are becoming increasingly common. Clients of wireless networks have continuously changing requirements for providers. In this project, a system to provide a sufficient signal for clients of a network as conditions change is proposed and validated. The system is comprised of hardware features such as a mobile access point and three heterogeneous client devices, and a movement algorithm. The mobile provider's autonomy is verified by the independence of initial position or orientation from success of the system. The system is designed for ease of reconfiguration; modularity in system design allows for advancements to be implemented simply and effectively.

1 Introduction

Wi-Fi enabled devices have become a ubiquitous aspect of society. Wi-Fi networks serve a variety of heterogeneous client systems, from laptops and smartphones connecting to and disconnecting from internet in a coffee shop to teams of heterogeneous mobile robots performing search and rescue missions. An inherent aspect of heterogeneous systems such as these is that some activities or devices will have different Wi-Fi requirements than others. Networks must provide high-quality signals regardless of variable client use conditions. Since needs for Wi-Fi propagation are dynamic, it follows that a Wi-Fi provider should have the ability to accommodate varying environmental conditions. This project seeks to achieve this by mobilizing a Wi-Fi provider.

Received signal strength indication (RSSI), measured in decibel-milliwatts (dBm), is commonly used because Ethernet infrastructure with off-the-shelf utility for measuring RSSI already exists in most indoor spaces [1][6]. However, due to fluctuations caused by phenomena such as multi-path fading and non-uniform propagation of radio signals, RSSI measurements can be unreliable. In [4], RSSI measurements are found too unreliable to be used as the sole source of indoor localization, but in [6] successful position estimation was obtained using wireless Ethernet signal strength. The algorithm proposed in this paper does not use RSSI measurements to determine distance or to localize. Therefore, while complications due to RSSI signal noise are present, they may not be as impeding in the physical realization of the algorithm.

J.-H. Kim et al. (eds.), *Robot Intelligence Technology and Applications 2*,
Advances in Intelligent Systems and Computing 274,
DOI: 10.1007/978-3-319-05582-4_81, © Springer International Publishing Switzerland 2014

A number of methods for exploration and optimization of sensor networks use mapping techniques to traverse an area, including mapping the gradient of RSSI values [13], and intentionally avoiding previously explored areas [14]. This project does not involve mapping the area of interest because RSSI values at specific points are expected to change over time given the changing needs of clients, therefore mapping would be ineffective. Our intent to enhance Wi-Fi signal of clients omni-directionally using robots without mapping capabilities is similar to that of [2], however we propose a more systematic algorithm than random movement.

This project proposes and validates an algorithm that enhances the Wi-Fi strength of a dynamic heterogeneous network such that the average RSSI value for all clients is within a predetermined allowable threshold. As in [5], this project provides a pattern-based algorithm which includes processing sensor information to dictate movements for traversing an area. This algorithm extends to many scenarios and conditions, such as mobile clients, different initial position and orientation of the mobile Wi-Fi provider, different weighting schemes for the clients, and different RSSI thresholds. The algorithm is simple enough to be implemented with a variety of mobile robots and easily adaptable for future improvements in RSSI collection and analysis as well as movement patterns.

The remainder of this paper is outlined as follows: Section 2 details the system configuration including hardware components, methods for RSSI collection and analyzation, and movement protocol. Section 3 includes a condition testing for the test environment and three test cases used to validate the algorithm. Section 4 provides insight for future works and applications. Section 5 concludes the paper with an overall evaluation of the algorithm.

2 Configuration

2.1 Provider and Clients

Provider. The mobile provider consists of a two-tiered shelf system on top of an iRobot Create (Fig. 1). Below the shelves is a 12V lead battery and a transformer to provide 24V of power. On the lower shelf is an Eee laptop, connected by an RJ-45 cable to the Power over Ethernet (PoE) network switch and by a serial connection to the iRobot Create. On the upper shelf is the PoE switch, given power by the battery and transformer, and providing the power to the PicoStation [9] access point (AP). The access point is positioned vertically above the center of the iRobot Create. The Ethernet connections are as such to set up the wired local area network (WLAN). The laptop accesses the PicoStation's TinyOS web interface through its connection to the switch. A bash script using the Linux "grep" command allows the laptop to read RSSI values from the access point using TinyOS. The laptop sends commands to the iRobot Create through an established serial connection. PicoStation RSSI value collection and iRobot Create movement are linked together by a C++ script executed by the laptop.

Clients. Three representative clients make up the heterogeneous team for this project. The DARwin-OP robot is a robot client with a wireless adapter. DARwin is a humanoid robot commonly used for research and education in robotics research [3]. The Nexus tablet is a human controlled device. The Edimax access point/range extender represents a packet-forwarding or routing device. The three clients, as well as the laptop and the PicoStation AP make up the WLAN.

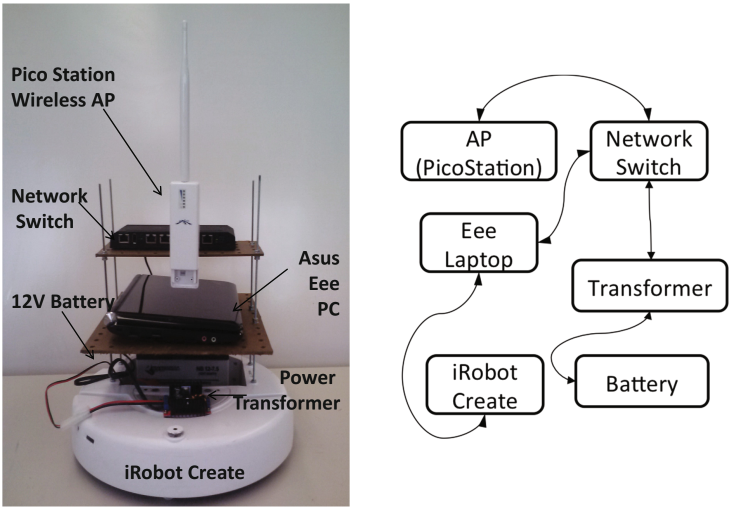


Fig. 1. Mobile Provider

2.2 Algorithm

Our algorithm consists of two procedures: current state analysis and a movement protocol. During current state analysis, RSSI values are obtained and analyzed to determine whether the average value is within the acceptable threshold, and if not, whether RSSI values are increasing. The movement protocol determines which action to take based on these results. The algorithm is constructed in such a way that it reacts in real-time to client movement, without reliance on a particular initial position or orientation of the mobile provider. It is easily adaptable for different client needs, such as the weighting scheme for clients and the overall acceptable threshold limit. A limited number of commands in the movement procedure make the algorithm adaptable for use with different robots. The separation of data collection and integration from physical movement commands allows for improvements in either to be implemented without needing to reconfigure the entire system.

Current State Analysis. At each time step, RSSI values are measured by the PicoStation for each client connected to the network. Each client device is given a weight which reflects its priority in the system. Test Cases 1 and 2 weight clients equally, and Test Case 3 examines the effect of different weighting schemes on provider movement. From this step on, the algorithm deals with this weighted average as the singular value to minimize.

An exponentially weighted moving average (EWMA) originally proposed in [10] is used to smooth inherent noise in RSSI measurements while maintaining priority of the most recent data (Eq. (1)). S_t represents the EWMA at time t, Y_t represents the data, in this case RSSI measurement averaged over the three clients, at time t. A constant λ is used to control the weight of the most recent datum at time t in relation to the previously calculated EWMA at time $t-1$. The selection of λ involves a compromise between detection delay and false alarms [7].

$$S_t = \lambda \cdot Y_t + (1 - \lambda) \cdot S_{t-1} \tag{1}$$

$$S_1 = Y_1 \tag{2}$$

To determine whether RSSI values are increasing, linear regression is performed on the 8 most recent RSSI averages. A trend line with a slope greater than 0 and standard error of regression slope greater than 0.05 is considered an increasing trend in RSSI measurements. These constraints vary by location and can be determined through preliminary testing in the experiment environment to recognize significant changes in RSSI. Validating optimization of these constraints for various environments is outside the intent of this project and is left for future research.

Movement Protocol. Figure 2 details the movement protocol for the provider. RSSI is measured continuously and noise is smoothed using the processes described above. If the RSSI value is within the threshold, the provider is sent a command to stay in place. If the RSSI value is above the threshold and not increasing, the provider is sent a command to move straight. If the RSSI value is above the threshold and increasing, the provider is sent a command to turn 90° counter-clockwise. Thus, with only three commands, the provider moves only when the average RSSI value is above the threshold, moves in directions of decreasing RSSI, and changes trajectory when RSSI values along are first found to be increasing.

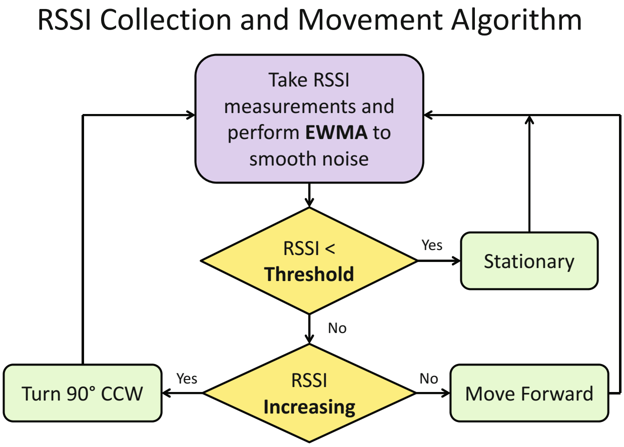


Fig. 2. RSSI Collection Analysis and Movement Algorithm

3 Experiment

The experimentation portion of this project involves condition testing to validate the choice of λ used in calculating the EWMA for the testing environment, followed by three test cases designed to isolate the effects of initial position, initial orientation, and weighting scheme of clients on the mobile provider's subsequent path. A trial is defined as successful if the provider reaches a location where threshold conditions are met (RSSI $<$ 42 dBm in this environment), and remains stationary for more than 10 seconds. The provider's speed is set to 0.2 meters/second (m/s) throughout the tests. The testing location is the ROTC armory at Purdue University in a room which measures roughly the dimensions of a football field. Our testing grid consisted of a 40 meters (m) x 40 meters (m) square.

3.1 Conditions Testing: Optimizing λ

The first experiment tests for an optimal λ value. The provider is sent down a straight path which goes between the three clients, and collects RSSI values along its path. This process is repeated for λ values of 0.1, 0.2, 0.3, 0.4, 0.5, 0.7, and 0.9. Figure 3 displays the outcomes of trials 0.1, 0.3, and 0.5 in order to highlight the effect of changing λ on the EWMA measurement trends. A λ of 0.5 is too large to smooth local noise in the RSSI values caused by unwanted phenomena, while a λ of 0.1 is so small that it inhibits the display of significant changes in RSSI caused by the movement of the provider. A λ of 0.3 is optimal as it captures the desired, global trend of RSSI but smoothes unwanted, local noise.

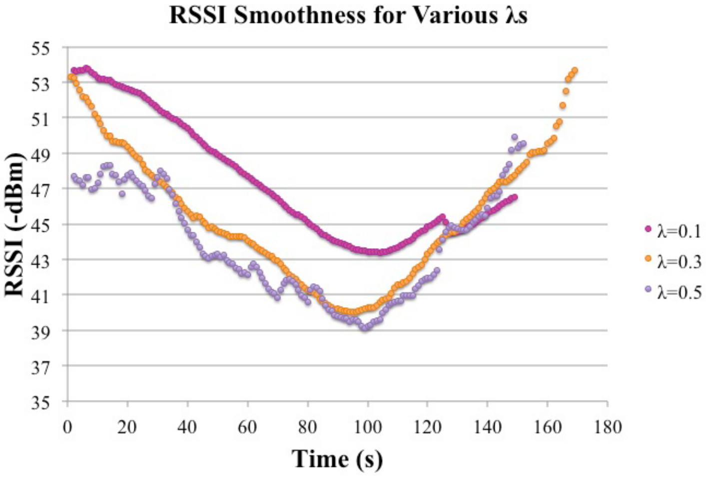


Fig. 3. Mobile Provider

3.2 Test Case 1: Varying Initial Position

The first test case assesses the effect of different initial positions of the provider. The mobile provider starts at 8 different points around the center of the configuration of clients as shown in Fig. 4. In all cases, the provider stops at a position within the threshold, validating that the success of the algorithm is largely independent of initial position. The average number of turns taken per path is 3.375, and the average time to reach the final location is 2 minutes, 50 seconds. The maximum number of turns taken is 8, and the maximum time taken is 6 minutes 30 seconds, both of which occur on the trial originating from the bottom left corner of the grid ($-16m$, $-7.5m$). In some trials, for example that originating at the top-right corner of the grid ($16m$, $27.5m$), the provider takes more than the minimum number of turns necessary to reach its final location, but in such cases the provider corrects quickly, and therefore the efficiency of the algorithm is not compromised.

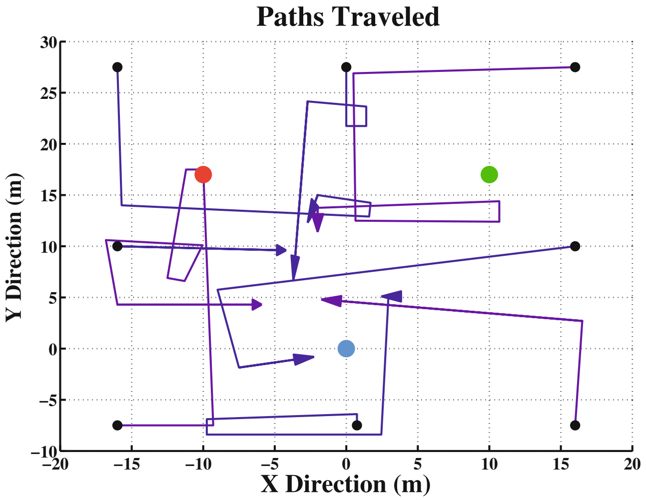
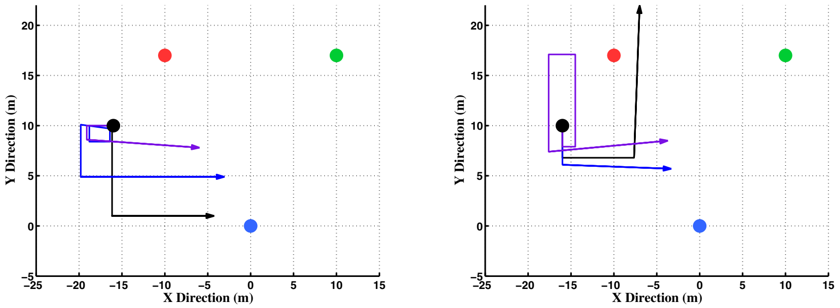


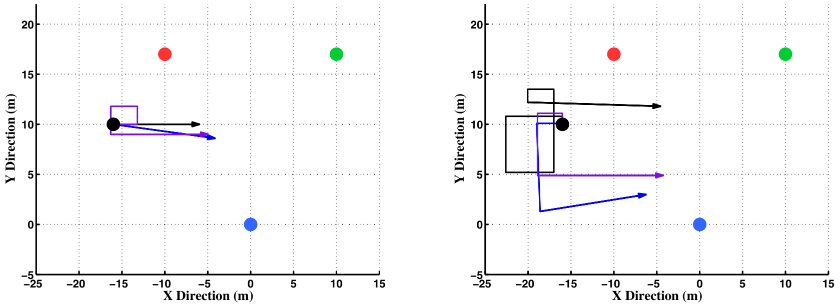
Fig. 4. Initial Positions

3.3 Test Case 2: Varying Initial Orientation

The second test case isolates the effect of initial orientation of the provider on the path taken. Three trials are performed with the provider starting facing each of the cardinal directions as shown in Fig. 5. Table 1 gives the number of turns taken for three trials facing each direction, the number of trials necessary to reach the final location of the provider, and the average time taken. Of the 12 trials, 11 are successful. In some trials,



(a) Facing South (b) Facing East



(c) Facing North (d) Facing West

Fig. 5. Provider Paths for Different Initial Orientations

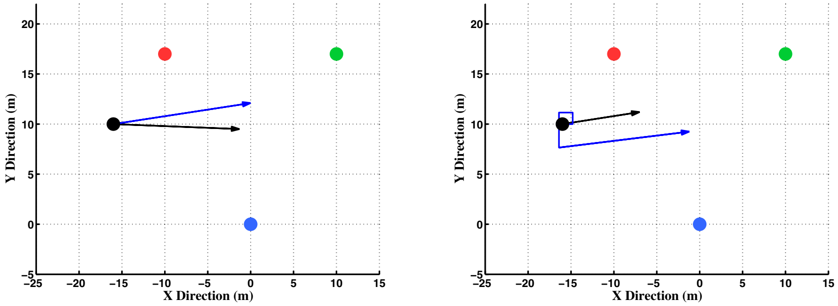
Table 1. Turns Taken and Necessary; Average Time for Different Initial Orientations

Orientation	East	North	West	South
Turns Taken	2 1 5	0 0 4	7 7 3	2 6 2
Turns Necessary	2 1 3	0 0 3	3 3 3	2 3 2
Average Time (min:sec)	2:32	1:17	2:56	2:14

the provider takes the most direct route, and in the others, mistakes are quickly corrected. In the first trial facing East, the provider moved off the grid without reaching a successful final location. The average time given for this orientation is the average of the second two trials. After examining the averaged RSSI values over time for this trial, the most likely cause of this is that RSSI values along the last leg of this path were in fact not increasing, and therefore the provider never changed direction. This serves as further proof that RSSI fields do not always follow expected gradient trends. Apart from this one trial, however, success was largely independent orientation.

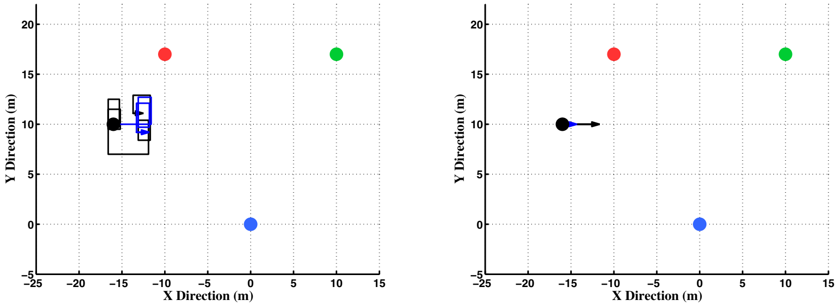
3.4 Test Case 3: Varying Client Weights

The third case tested the the effect of different schemes for weighting clients (Fig. 6). Figures 6 (a)-(e) show two trials for each of the paths taken for five different weighting weighting schemes. Figure 6 (f) shows the variability of RSSI per client while the mobile provider remains stationary at its starting position for a period of about 3 minutes



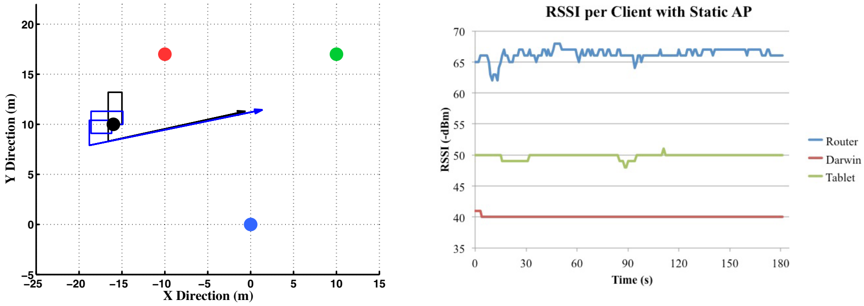
(a) $R = 1$; $D = 1$; $T = 1$

(b) $R = 1$; $D = 4$; $T = 4$



(c) $R = 6$; $D = 1$; $T = 1$

(d) $R = 1$; $D = 6$; $T = 1$



(e) $R = 1$; $D = 1$; $T = 6$

(f) RSSI variability per Client

Fig. 6. Provider Paths for Different Client Weights. (R = Router, D = DARwin, T = Tablet. Stars mark clients with the highest weights in each scheme.)

$(-16m, 10m)$. The standard deviations of RSSI values from the devices to the provider over this period are as follows: $\sigma_{DARwin} = 0.147$, $\sigma_{tablet} = 0.400$, and $\sigma_{router} = 0.924$.

The most efficient schemes were that in which all clients were weighted equally, (Fig. 6 (a)), that in which the router is weighted less than the other two clients (Fig. 6 (b)), and that in which DARwin is weighted more than the tablet and the router (Fig. 6 (d)). In each of these three schemes, success is reached in both trials, for a total of six successful trials. While both trials for the scheme in which the tablet is weighted more than DARwin and the router are ultimately successful, these trials are not as efficient, as paths double back on themselves (Fig. 6 (e)). In the scheme that weights the router more than DARwin and the tablet, success is not reached in either trial, and paths double back on themselves multiple times (Fig. 6 (c)). Consulting the variability of RSSI signals from each client (Fig. 6 (f)), it is evident that paths are most efficient when clients with lower signal variability are given higher weight (Figs. 6 (a), (b), (d)) and less efficient when clients with higher signal variability are given higher weight (Figs. 6 (c), (e)).

Each client had a different average RSSI value during static testing (Router 66.25 dBm; DARwin 40.02 dBm; Tablet 49.85 dBm). Since the router's average RSSI value of 66.25 was much higher than the testing threshold of 42 dBm, it is realistic that when weighted the router is weighted the most, the threshold condition would never be met. However, we would expect the provider to find a position more optimal for the signal strength of all clients, rather than double back multiple times near its starting location as in Fig. 6 (c). Therefore, while reaching a threshold of 42 dBm may not have been realizable in this trial, the motion taken by the provider suggests that the noise of individual clients has a significant influence on provider path.

4 Future Works and Applications

Adaptability is a key focus of this project. Modularity between data collection, data analysis, and movement protocol allows for improvements in a certain process to be implemented without reconfiguration of the algorithm at large. The algorithm could easily be adapted to measure parameters other than RSSI for connection strength, for example signal quality or throughput. Improvements in smoothing raw data values and interpreting them or in the movement protocol could increase efficiency and reduce the time and energy consumptions for reaching an allowable threshold. This system could also be applied to different environments, in which case constraints and thresholds should be re-evaluated. Multiple APs could be used to create a robotic mesh network in a larger environment as suggested in [8] and [12]. The algorithm could easily be adjusted to accept new clients and account for clients leaving, furthering possibilities for applications involving dynamic systems.

An unavoidable consequence of using mobile robot communication is the possibility of malicious destructive intrusion to the system. Prior to implementation, validating a secure connection between mobile robots of the same network is particularly important. Suggestions for secure implementation detailed in [11].

5 Conclusion

This project validates an algorithm for enhancing the strength of signal connections between a Wi-Fi provider and clients by mobilizing the provider. The algorithm involves current state collection and analysis of RSSI values, which relies on location-dependent constraints, and a simple movement protocol. Since the algorithm is a heuristic method involving pattern-based algorithms, the path taken by a mobile provider is often not the most efficient possible toward the allowable RSSI threshold, however the algorithm is efficient and timely enough to be effective in a physical real-time environment. The algorithm is validated by a high success rate for a variety of initial positions and initial orientations of the mobile provider. This resistance of the algorithm to initial conditions simplifies deployment for the user. The main contribution of this work is the presentation and physical realization of a system that successfully implements a modular design for enhancing Wi-Fi multi-directionally, which easily accommodates future improvements and implementations.

References

1. Chang, N., Rashidzadeh, R., Ahmadi, M.: Robust Indoor Positioning Using Differential Wi-Fi Access Points. IEEE Transactions on Consumer Electronics 56(3), 1860–1867 (2010)
2. Correll, N., Bachrach, J., Vickery, D., Rus, D.: Ad-hoc Wireless Network Coverage with Networked Robots that Cannot Localize. In: IEEE International Conference on Robotics and Automation, ICRA 2009, pp. 3878–3885. IEEE (2009)
3. DARwIn robot: Robotis (2013), `http://robotis.com`
4. Dong, Q., Dargie, W.: Evaluation of the Reliability of RSSI for Indoor Localization. In: 2012 International Conference on Wireless Communications in Unusual and Confined Areas (ICWCUCA), pp. 1–6. IEEE (2012)
5. Hayes, A.T., Martinoli, A., Goodman, R.M.: Distributed Odor Source Localization. IEEE Sensors Journal 2(3), 260–271 (2002)
6. Ladd, A.M., Bekris, K.E., Rudys, A., Kavraki, L.E., Wallach, D.S.: Robotics-based Location Sensing Using Wireless Ethernet. Wireless Networks 11, 189–204 (2005)
7. Lucas, J.M., Saccucci, M.S.: Exponentially Weighted Moving Average Control Schemes: Properties and Enhancements. Technometrics 32(1), 1–12 (1990)
8. Pabst, R., Walke, B.H., Schultz, D.C., Herhold, P., Yanikomeroglu, H., Mukherjee, S., Viswanathan, H., Lott, M., Zirwas, W., Dohler, M., et al.: Relay-based deployment concepts for wireless and mobile broadband radio. IEEE Communications Magazine 42(9), 80–89 (2004)
9. PicoStation: Ubiquiti Networks (2013)
10. Roberts, S.W.: Control chart tests based on geometric moving averages. Technometrics 1(3), 239–250 (1959)
11. Stoleru, R., Wu, H., Chenji, H.: Secure neighbor discovery and wormhole localization in mobile ad hoc networks. Ad Hoc Networks 10(7), 1179–1190 (2012)

12. Tekdas, O., Yang, W., Isler, V.: Robotic Routers: Algorithms and Implementation. The International Journal of Robotics Research 29(1), 110–126 (2010)
13. Twigg, J.N., Fink, J.R., Yu, P., Sadler, B.M.: RSS Gradient-Assisted Frontier Exploration and Radio Source Localization. In: 2012 IEEE International Conference on Robotics and Automation (ICRA), pp. 889–895. IEEE (2012)
14. Zhang, X., Sun, Y., Xiao, J., Cabrera-Mora, F.: Theseus gradient guide: An indoor transmitter searching approach using received signal strength. In: 2011 IEEE International Conference on Robotics and Automation (ICRA), pp. 2560–2565. IEEE (2011)