ADDING DIRECTION TO A DIRECTIONLESS WORLD

BY

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THESIS

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ABSTRACT

This thesis focuses on the feasibility of adding a new dimension to spatial context referred to as orientation. Based on directional antennas and previous work in RSSI based radio distance estimation, this work shows that using directional antennas alone, the angle between two devices can be approximated. Furthermore, this thesis shows the effect of distance estimation error on angle estimation and how the number of samples affects the error in angle estimation.

To my wife, family and friends, for their love, support,
and always making me smile.

ACKNOWLEDGMENTS

This work was made possible by the support of my advisor, Robin Kravets, and my groupmates, Farhana Ashraf, Mehedi Bakht, and Riccardo Crepaldi.

Special thanks goes to CS 424 which inspired the idea of using Roombas, Steve Lumetta who always made me want to be better than I was, and Wade Fagen who kept me sane while teaching. Finally, thanks goes to the University of Illinois for giving me some of the best six years of my life.

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CHAPTER 1

INTRODUCTION

As computing devices have become both ubiquitous and more mobile, the opportunities for computers to augment human lives have increased. In order for mobile devices to make decisions relevant to our current activity, they require context. This area of work is known as context-based computing and it focuses on having computing resources make intelligent decisions based on our lives. Context can refer to many different variables in our lives such as time, temperature, vital signs, or location. An operation which might be acceptable in one context might be considered unacceptable in another such as playing a loud email notification while you are asleep.

In the mobile space, location is the dynamic feature of context which we would like to be tracked. The process by which a device discovers its spatial context is known as localization. Knowing the location of our mobile device allows for the screen to be turned off when the device is in our pocket or the volume to be reduced when listening to a presentation. In practice, we would like the context to be always available and require little to no user input.

Previous work on localization has focused on different types of spatial context. Absolute geographical location, which can be represented with a latitude and longitude, indicates the physical location of the user but does not indicate anything about the user's surroundings. Alternatively, relative location focuses on the user's location with respect to other points. This allows for answers to questions such as, "Are any of my friends nearby?" or "Which exit will have the least congestion?".

These solutions have one common assumption, that a user can be represented by a single point. This assumption ignores the fact that our orientation is often just as important as our location. Human interaction is defined primarily by our orientation rather than our spatial proximity.

An example scenario might be at a professional conference where you meet many people. You would like to share your contact information with anyone you talk to for more than 10 minutes. Without orientation your contact information will be shared indiscriminately with anyone standing beside or behind you. Clearly there is a gap between what can currently be expressed and the true context of a situation caused by the lack of orientation information.

This thesis focuses on the feasibility of adding a new dimension to spatial context, orientation. Using directional antennas, the angle between two devices can be inferred and delivered to higher layer applications, which take advantage of the information. This work shows that using antennas alone, the angle between two devices can be approximated within 40 degrees. Furthermore, this thesis shows the effect of distance estimation error on angle estimation and how the number of samples affects the error in angle estimation.

The remainder of this thesis will discuss orientation estimation. Chapter 2 discusses previous techniques of location estimation and how they can be applied to orientation estimation. Chapter 3 details the design of a system offering orientation context which is then evaluated in Chapter 4. Finally, Chapter 5 summarizes this thesis and presents future directions for orientation estimation.

CHAPTER 2

RELATED WORK

Much of the existing work done in location estimation systems can be reused when estimating orientation. Localization is comprised of several use cases of which only some will be useful to orientation. The different use cases are demonstrated by the following scenarios.

The most common application of localization is obtaining absolute geographic position. This type of localization is meant to answer the question, "Where am I?". This paradigm was made popular by GPS-enabled devices used to deliver directions. Navigation requires the absolute geographic position of the device which it then overlays on static maps. This scenario is interesting because navigation systems typically display orientation as well as location. This orientation is commonly generated based on assumptions about the mobility model and the availability of absolute position. The orientation is generated by making a vector from the current position and previous position. This works well for driving, but can be fooled by simple tasks such as driving the car in reverse gear. These errors could be solved by using a digital compass instead. Acquiring absolute locations from GPS has energy costs and so this works well only when energy is not a concern, the path avoids covered areas (tunnels, etc.) and the environment is relatively static (store doesn't move).

A new area of localization has recently become popular known as relative positioning which answers the question, "What's around me?". An example scenario involves a firefighter rushing into a burning building in order to find a victim trapped inside. Once the firefighter has the victim they want to leave the building by the same path they entered. One solution would be for the firefighter to drop beacons along their ingress path. When leaving, the firefighter could then retrace their path using the beacons. In this scenario, the location of a beacon is only important in relation to the next beacon.

Relative positioning produces an accurate map within a translation, where in the world we are, and a rotation, which direction is north. Previous work [1, 2, 3, 4, 5] has shown how a relative positioning system can use anchors to create an absolute geographic map. Relative positioning is orthogonal to the problem this thesis solves. A system could make use of both kinds of context.

A specific instance of relative positioning which is only concerned with single hop measurements is known as proximity detection. An example scenario involves a child's game where one child hides and the other seeks. The twist is that there is an omniscient helper which gives a hot/cold reading to the seeker. In this game the proximity of the seeker to the hider makes the feedback change. The proximity of the two players can be measured by the proximity of their two devices. This proximity measurement is known as distance estimation [6, 7, 8]. This thesis will make use of distance estimation, but will also present the direction of the hider in the game, a definite advantage.

2.1 Techniques and Technologies

Localization has been studied extensively in the past. These systems share a common subset of components, but tend to be optimized for specific problem domains which disallows any one best protocol from existing. A comprehensive overview of the area can be found in [9].

2.1.1 Distance Estimation

Underlying all localization is a distance estimate between the device and a point of interest. These estimates are based on the sensors available to the device. Each sensor has an energy cost, accuracy, and coverage associated with it. For example, GPS has a high energy cost, better than 10m accuracy when combined with static maps, and coverage most everywhere but indoors. A summary of the available sensors for distance estimation is given in Table 2.1 along with citations for existing work which leverage the technology.

Sensor	Power (mW)	Accuracy (m)	Coverage (m)
Radio			
WiFi [10, 11, 8]	1000	3	100
Bluetooth [12, 13, 14]	200	1	15
ZigBee [15, 16, 17]	500	2	25
Infrastructure			
GPS [18]	1500	10	Outdoors
GSM [19, 20, 21]	30	1km	Everywhere
Misc.			
Ultrasound [22, 23, 24]	25	1	10
Infrared [25]	40	-	Line of Sight
RFID [26, 27]	1	1	1
Accelerometer [28, 29]	50	10%	-
Magnetometer [29]	60	Unique Points	-

Table 2.1: Comparison of Positioning Sensors

2.1.2 Radio-based Distance Estimation Techniques

Within radio-based distance estimation, a variety of approaches have been proposed by previous work. Time of arrival [30], time difference of arrival [31, 32, 33], and angle of arrival [34, 35, 36] all require the devices to be closely synchronized or to have space for large arrays of antennas. Synchronization can be solved using messaging between devices, but that can drain batteries quickly. Angle of arrival requires an array of antennas to detect the direction of reception. These antennas have to be spaced apart which makes the entire array take up a great deal of space. Based on these issues, received signal strength (RSSI) distance estimation is used.

2.1.3 RSSI-based Distance Estimation

Radio signal strength based distance estimation rests upon the underlying radio layer's characteristics. This work uses the popular *two-ray ground reflection* propagation model, where the signal strength decreases as the fourth power of the distance. This can be modeled as $p_{rx} = \frac{p_{tx}}{d^4}$, where p_{rx} is the received power, p_{tx} is the transmitted power, and d is the distance between the devices. In all RSSI based distance estimation techniques, p_{tx} is either kept constant or transmitted to the receiver so the receiver can account for it.

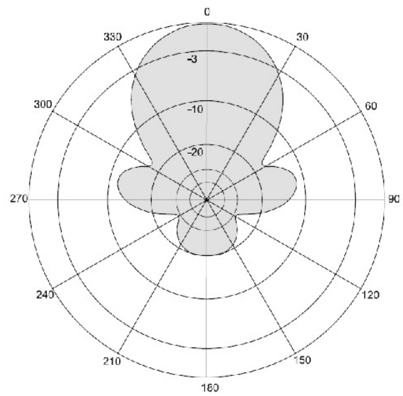


Figure 2.1: Directional Antenna Pattern

2.1.4 (Omni)Directional Antennas

The signal strength of a radio is based on the gain of the antenna which can be modeled as $g(r, \theta)$ in two-dimensional polar coordinates. Omnidirectional antennas do not depend on the angle and can be modeled as $g(r)$. The gradient of the gain pattern for a directional antenna affects how accurate angle measurements will be. Larger gradients are more easily detected, because of the bigger difference in measurements between angles. Figure 2.1 shows one such pattern. Ideally, we would like to see an ellipse like shape to give a smooth decreasing function.

2.2 Radios

For orientation we are interested in radio-based signal strength techniques so we look specifically at WiFi, Bluetooth and Zigbee. Signal strength readings are based on the energy received in the signal of a packet. Many protocols have variable power transmission protocols to help with hidden-terminal problems so it is important to fix the transmission power. In general this can be done using discovery mechanisms which use the highest power broadcasts possible and small packet sizes. Figures 2.2, 2.3 and 2.4 show signal strength measurements at various distances for the different radios. Tighter distribution bars allow for better estimates.

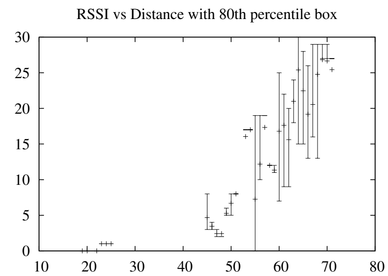


Figure 2.2: WiFi Distance Estimation

2.2.1 WiFi

WiFi is one of the most commercially successful wireless standards which also means that it is one of the most prolific. Its discovery mechanism is based on a probe request/response combination sent at a fixed bit rate and power. Because the probe responses are sent at a fixed power, the RSSI from a probe request is more reliable than from an established association. WiFi was designed to operate at up to 100 meters, but requires a great deal of energy to stay awake at all times.

2.2.2 Bluetooth

Bluetooth is a standard designed for short-range (<10m) low bandwidth applications. The MAC layer employs a frequency hopping sequence which allows for collision avoidance since the standard operates in the same ISM band as WiFi. This frequency hopping scheme makes the discovery process a bit more difficult as a given device could be on any of the 32 channels. Bluetooth's inquiry must search multiple sets of channels which can take up to 12 seconds. For Bluetooth it is important to use the discovery process to avoid the security involved with establishing a connection.

2.2.3 ZigBee

ZigBee is a low power, low bandwidth radio designed for embedded devices such as sensor motes. Cost and memory space necessitate a simple MAC layer which gives ZigBee the shortest discovery process of all the radios. The discovery process is defined by higher layer protocols, but for the purposes

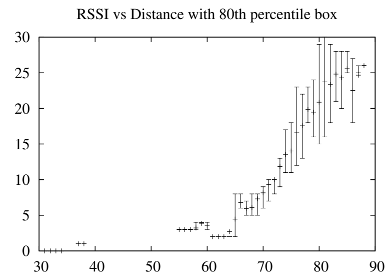


Figure 2.3: Bluetooth Distance Estimation

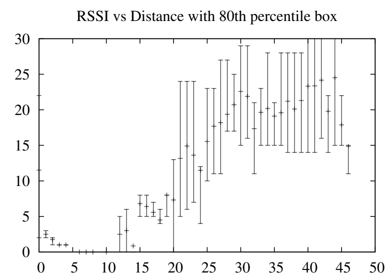


Figure 2.4: ZigBee Distance Estimation

of this thesis, each device sends a broadcast beacon periodically at a fixed power level to announce its presence.

2.3 Multiple Radios

Recently, work has been done to overcome the shortcomings of single sensor platforms by combining multiple sensors [37]. Virtual Compass [38] intelligently selects between using Bluetooth and WiFi for distance estimates which incorporate error margins. By including the error estimates, [38] is able to take the union of the two radio's coverage and the better accuracy. This work uses the simpler one radio approach due to physical device constraints, but could take advantage of such an approach for both distance and angle estimation.

CHAPTER 3

DESIGN AND IMPLEMENTATION

This thesis presents an angle estimation system that is based on directional antennas and received signal strength. Underneath, the estimation is computed in two stages. The first stage uses a standard unidirectional antennae to discover the relative distance between two devices. The second stage takes the distance estimate and combines it with a signal strength measurement from a directional antenna. Together, these combine to form an angle measurement based on the expected signal strength for a given distance.

3.1 Distance Estimation

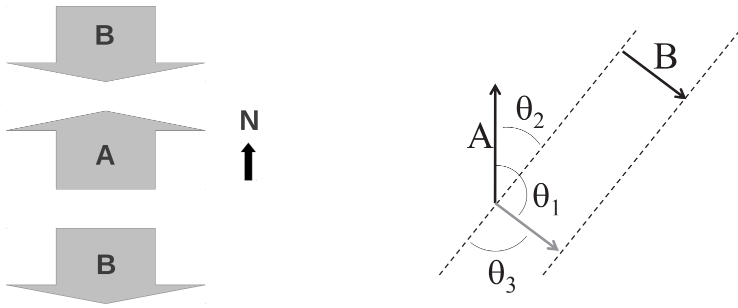
The design of the distance estimation system is based on previous work as described in Section 2.1.3.

3.2 Orientation Estimation

Determining the orientation of a device relies upon accurate angle measurements which are presently not available on commodity hardware.

3.2.1 Orientation Aliasing

Digital compasses alone are insufficient to compute the relative orientation of two devices. Consider two devices shown in Figure 3.1a, one facing north and one facing south. The devices might be facing each other or facing away from each other. Absolute location would solve this problem but has high energy costs and is generally unavailable indoors. Radios acting as sensors to determine the direction can be used in conjunction with digital compasses



(a) Orientation Aliasing (b) Angle Diagram

Figure 3.1: Orientation Figures

to produce accurate orientation estimates.

Figure 3.1b describes the measurements available from directional antennas, θ_2 θ_3 and a compass, θ_1. The equation $\theta_1 + \theta_3 - \theta_2 = 180\,\text{deg}$ defines a linear relationship between the three measurements. The equation overconstrains the system and can be used to reduce the error or to solve for one of the measurements instead of measuring it.

Presented in this thesis is the accuracy of a single measurement, θ_2 or θ_3. Note that each device is designed to have a directional and omnidirectional antenna so measurements are taken between A's directional antenna and B's omnidirectional antenna. Presently, no off-the-shelf device has a directional antenna capability so the experiments are simulated using a makeshift antenna reflector external to the device.

In reality, signal strength measurements tend to be very noisy and often don't follow analytical models very closely due to multi-path fading and other environmental effects. Using a makeshift reflector with no known model only compounds the unpredictability of the signal strength measurements. In order to make accurate estimates, models based on approximations of reality are used.

3.2.2 Lookup Tables

The simplest approach to approximation requires storing lookup tables to convert between *(omnidirectional RSSI, directional RSSI)* and *(distance, angle)* pairs. The values to fill in this lookup table are generated by using polynomial regression on the measured samples. Lookup tables represent

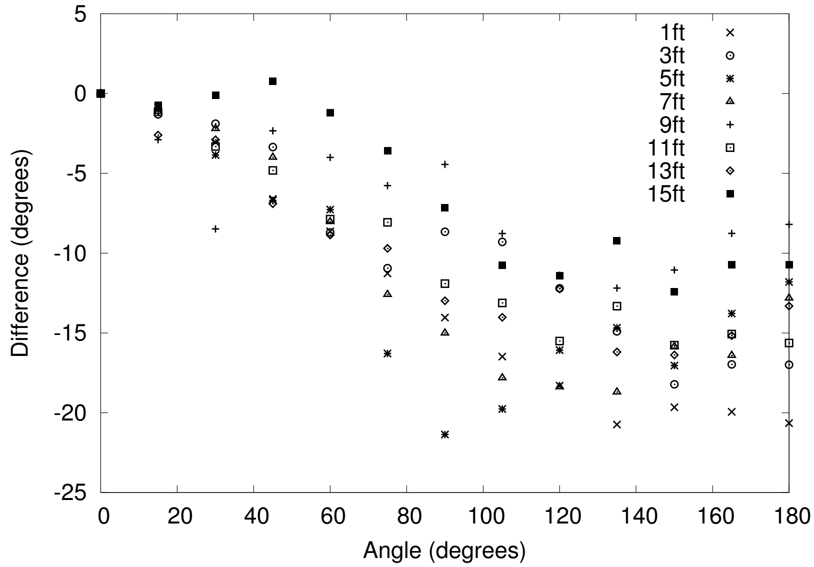


Figure 3.2: Relative Angle Measurements

the inverse function in $d = f^{-1}p_{rx}$. By storing values, the function does not have to be continuous and can more closely match the observed distribution.

3.2.3 Relative Estimation

On devices with limited memory, it might not be desirable to hold the lookup table in memory. In this case, the system can monitor the difference between the directional and omnidirectional measurements to determine the angle at which the device resides. Figure 3.2 shows the difference in means for different distances and angles. Because the difference between the directional and omnidirectional readings does not have a constant difference for different distances, this estimation approach will incur additional error.

3.3 Implementation

The goal of implementing the system was to support monitoring of short range social interactions. The performance of the system is highly dependent on the selection of radio interface. ZigBee, being ultra low power, suffers from high variability in measurements at larger distances [39]. WiFi is too high power where short ranges show very little variation in signal strength.

	Contacts	Latency (s)
hcitool scan	1	10
custom hci listener	3-8	1

Table 3.1: Comparison of Bluetooth Inquiry

Because we are only concerned with 15ft and less, Bluetooth is the ideal radio.

In order to get the most accurate signal strength estimator, the Bluetooth inquiry with RSSI HCI command is used, which was first defined in Bluetooth 2.1. In general, several contacts are made between two devices during the discovery process. The default Linux Bluetooth stack Bluez reports the last of all of these contacts. In order to collect samples faster, a direct HCI call and listener were used, which allowed for an 8-10x gain in reported contacts. By reporting contact events immediately rather than accumulating them, latency is reduced from eight seconds to less than one second.

CHAPTER 4

EVALUATION

The goal of the evaluation is to decide if the angle of a target device can be detected by the source with enough precision to determine social interaction. In the worst case, we would like to be able to say whether the device is facing or not facing the target device. The performance of the system is based on the following metrics:

- The mean error in distance estimation.
- The mean error in angle estimation at a fixed distance.
- The mean error in angle estimation based on an estimated distance.

We are not concerned with the performance of the distance estimation system except for how it affects the combined angle estimation system. By looking at the angle estimation for a fixed distance, we can see the best angle estimation possible given perfect distance estimation. Perfect estimation is not practical, so we show how the error in distance estimation affects the angle estimation system. In conjunction with the three metrics, we explore how the number of samples affects the quality of the measurement.

4.1 Methodology

All experiments shown were conducted indoors in an apartment hallway using Nokia N900 phone's [40] Bluetooth radio. The N900 phones run a Linux based operating system presenting the same interface as a laptop running Debian Linux. Tests were also run with Google Nexus S phones [41] in an office environment with similar results. In order to automate collecting a large number of samples at different angles and distances, a Create Roomba [42] with serial interface was used to move one device. The static device was placed on a table approximately three feet above the ground while the mobile device was placed on a tripod on top of the Roomba. For tests requiring a directional antenna, an empty lined chips can was used as the reflector.

4.2 Measurements

All estimation and evaluation was done on a set of 12,152 data points taken at 2 foot intervals from 1 to 15 feet and angle intervals of 15 degrees from 0 to 180 degrees. This is approximately 120 measurements per position.

4.2.1 Angle Estimation

In order to translate between signal strength (RSSI) and angle, regression is used on the collected samples for a given distance. Least squares polynomial regression of order 4 is used to generate the translating function. Shown in Figure 4.1 is the transfer function for a 1 foot distance. The solid line represents the estimated transfer function from RSSI to angle and the hash marks represent the underlying samples which are being approximated.

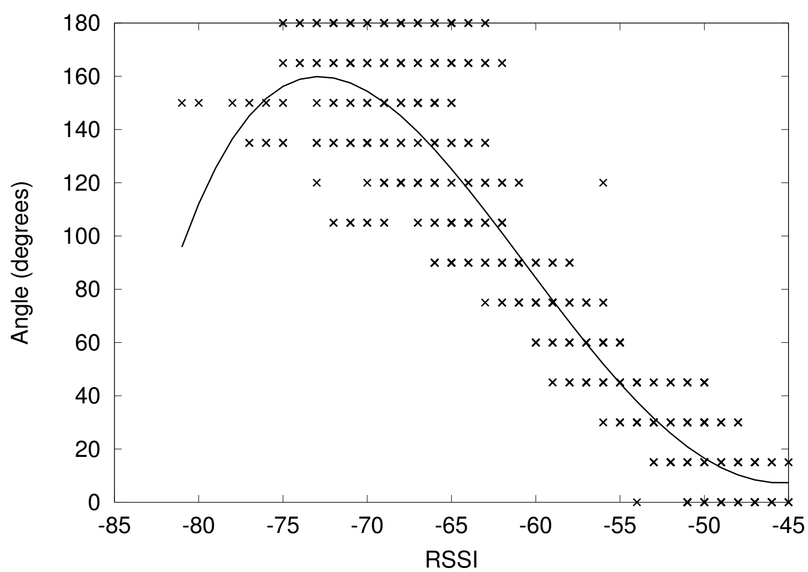


Figure 4.1: Angle Estimation at 1ft

4.2.2 Angle Error

The estimated transfer function contains a certain amount of error from what the observed measurements were. The error in angle estimation is calculated as *Estimated Angle - Actual Angle.* A positive error means that the estimation was too high. The boxes in Figure 4.2 show the inner quartiles and the whiskers represent points outside of the range. A dotted line showing no error was added for clarity. As seen in Figure 4.2, the accuracy is better for smaller angles. For angles less than 30 degrees, we can confidently state that the devices are facing and for larger angles we can state that the devices are not facing. The increased error in larger angles is an effect of directional antennas having a sharp drop-off when unaligned with the target device (See Figure 2.1). Directional antennas with a more linear angular dependency might have better performance for larger angles. The angle approximation is based on the assumption that the distance can be estimated perfectly. Next, we will consider distance estimation and how it affects the angle estimation error.

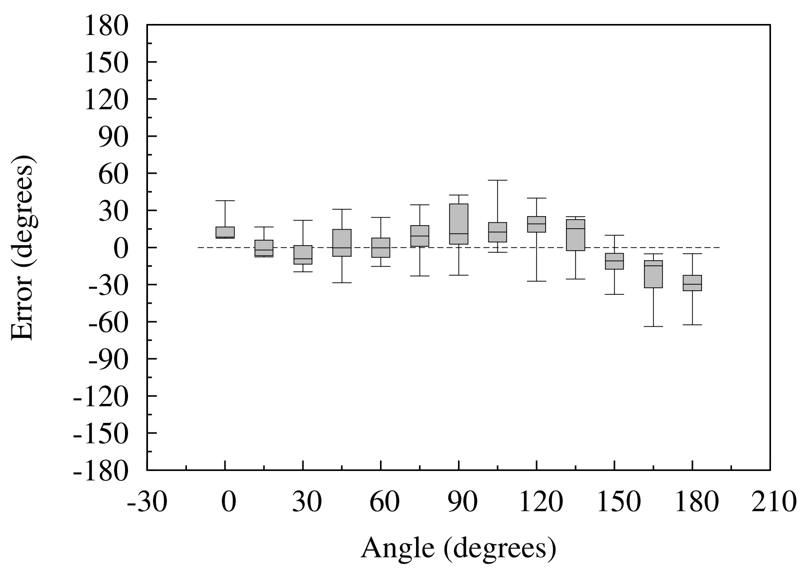


Figure 4.2: Angle Error at 1ft

4.2.3 Distance Estimation

Distance measurements tend to be noisier than angle measurements, as shown in Figure 4.3, which causes rather large error bars in Figure 4.4. The mean error from Figure 4.4 is 1.8 feet which is in line with previous work when the smaller interval is considered. These distance estimates allow the system to decide which angle transfer function to use by looking at previously collected RSSI samples from the same distance, but will introduce more error into the system.

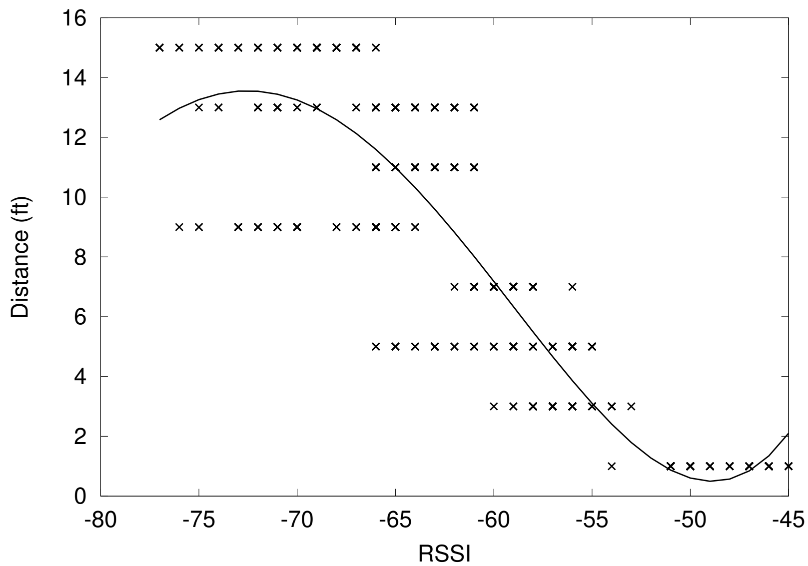


Figure 4.3: Distance Estimation

4.2.4 Combined Angle Error

In order to determine the effects of error in the distance estimation on the accuracy in angle measurement, a combined error measurement is taken. This is calculated by randomly selecting a omnidirectional measurement taken at the same distance, estimating the distance based on the omnidirectional reading, and then calculating the estimated angle transfer function at that distance. Finally, the estimated angle is compared to the actual angle shown in Figure 4.5. Due to poor distance estimation, the measurement shows a great deal of error, up to 180 degrees in Figure 4.5c. Based on this, a single sample alone would not suffice to say anything about the orientation of the

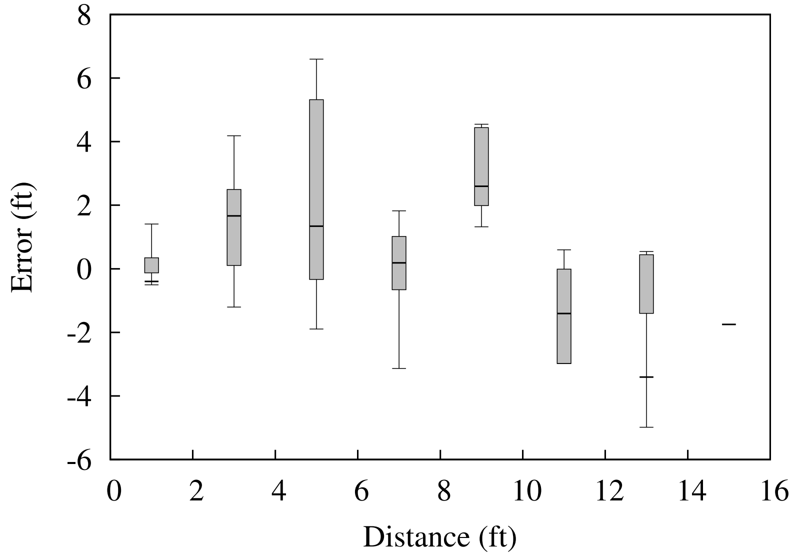


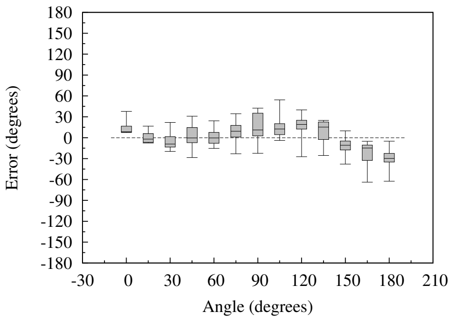
Figure 4.4: Distance Error

two devices.

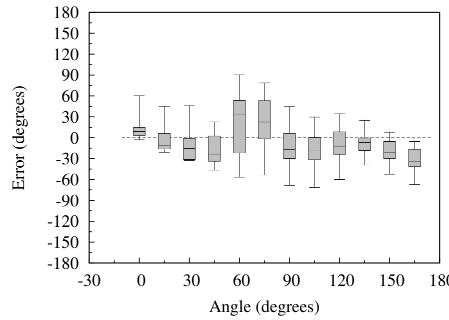
In order to reduce this error we took multiple RSSI samples, threw out the max and min, and then found the mean of the remaining samples. Figure 4.6 shows improvement with just three samples, but some amount of error still exists. Figure 4.7 shows a significant improvement with ten samples, especially for the inner quartiles shown as the boxes. This figure shows that in a real world scenario the angle can be detected within 30 degrees for almost all distances. This accuracy is sufficient for applications such as monitoring social interactions, but not good enough to direct a robot through a maze or other fine grained tasks.

4.3 Summary

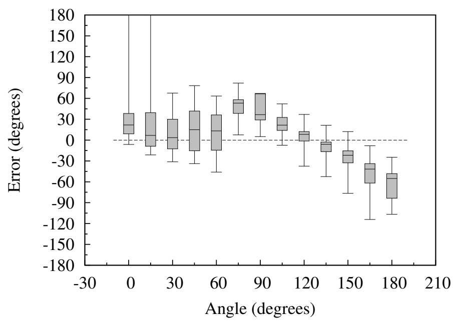
The goal of the system was to determine whether radio based techniques could be used to approximate relative orientation of two devices. Based on the collected samples, the answer is yes if enough samples are used. With a mean error below 40 degrees for all distances, the system can give an accurate reading as to whether two devices are facing each other or not even with a sub par distance estimation system.



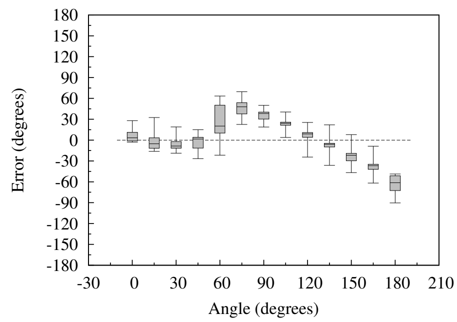
(a) At 1ft



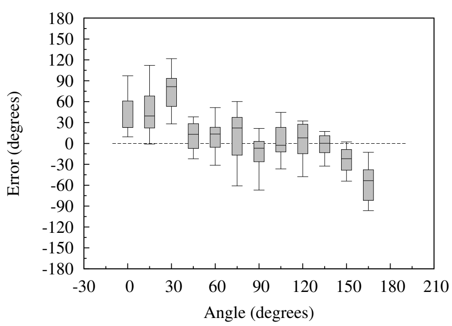
(b) At 3ft



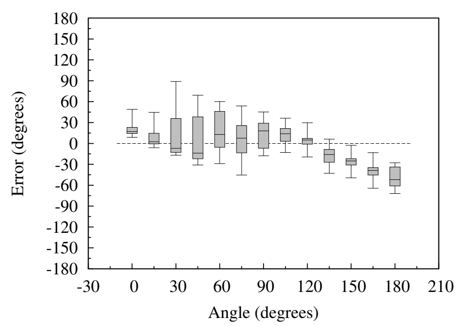
(c) At 5ft



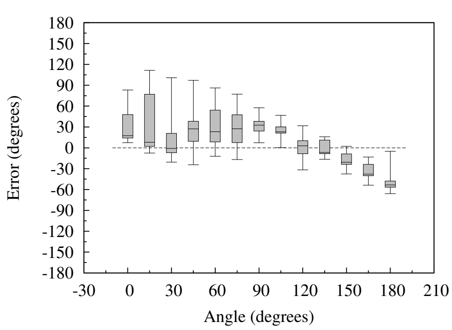
(d) At 7ft



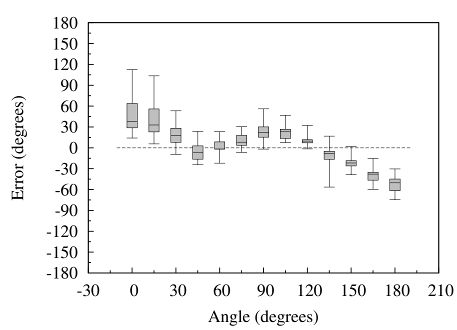
(e) At 9ft



(f) At 11ft

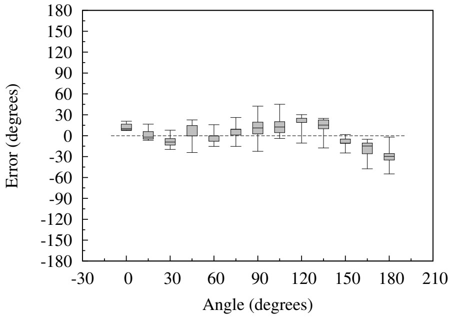


(g) At 13ft

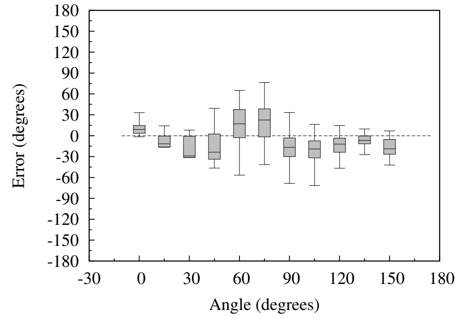


(h) At 15ft

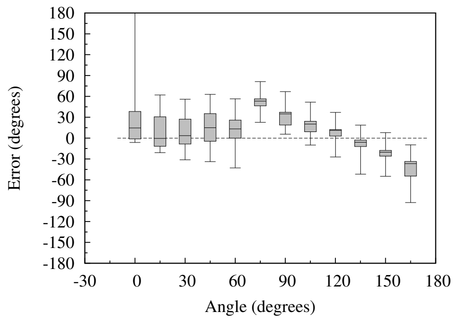
Figure 4.5: Combined Angle Error



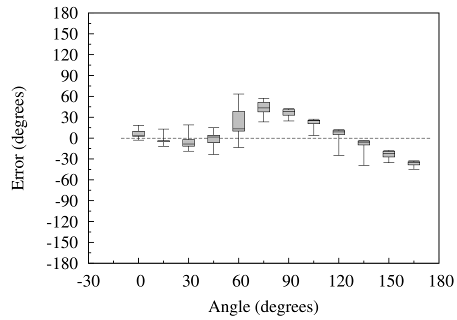
(a) At 1ft



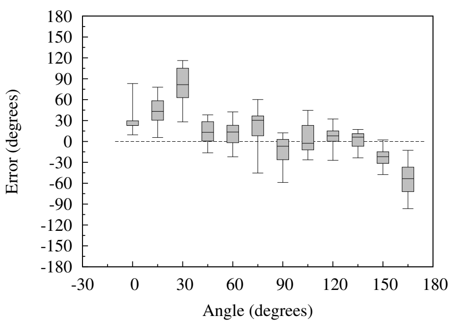
(b) At 3ft



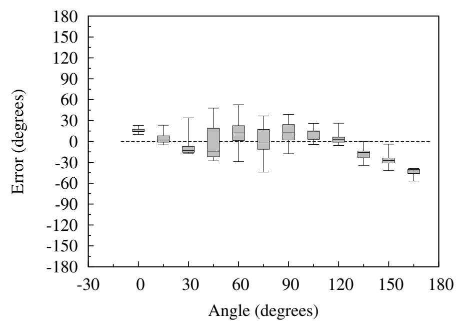
(c) At 5ft



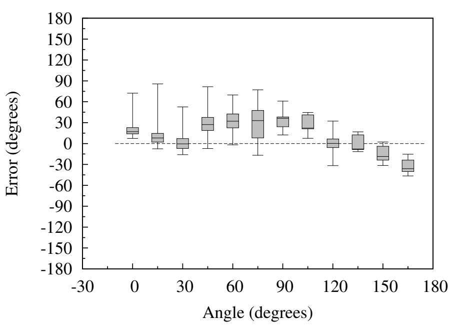
(d) At 7ft



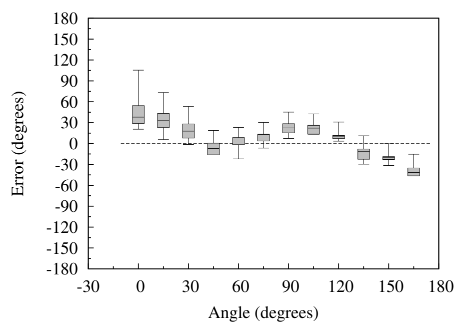
(e) At 9ft



(f) At 11ft

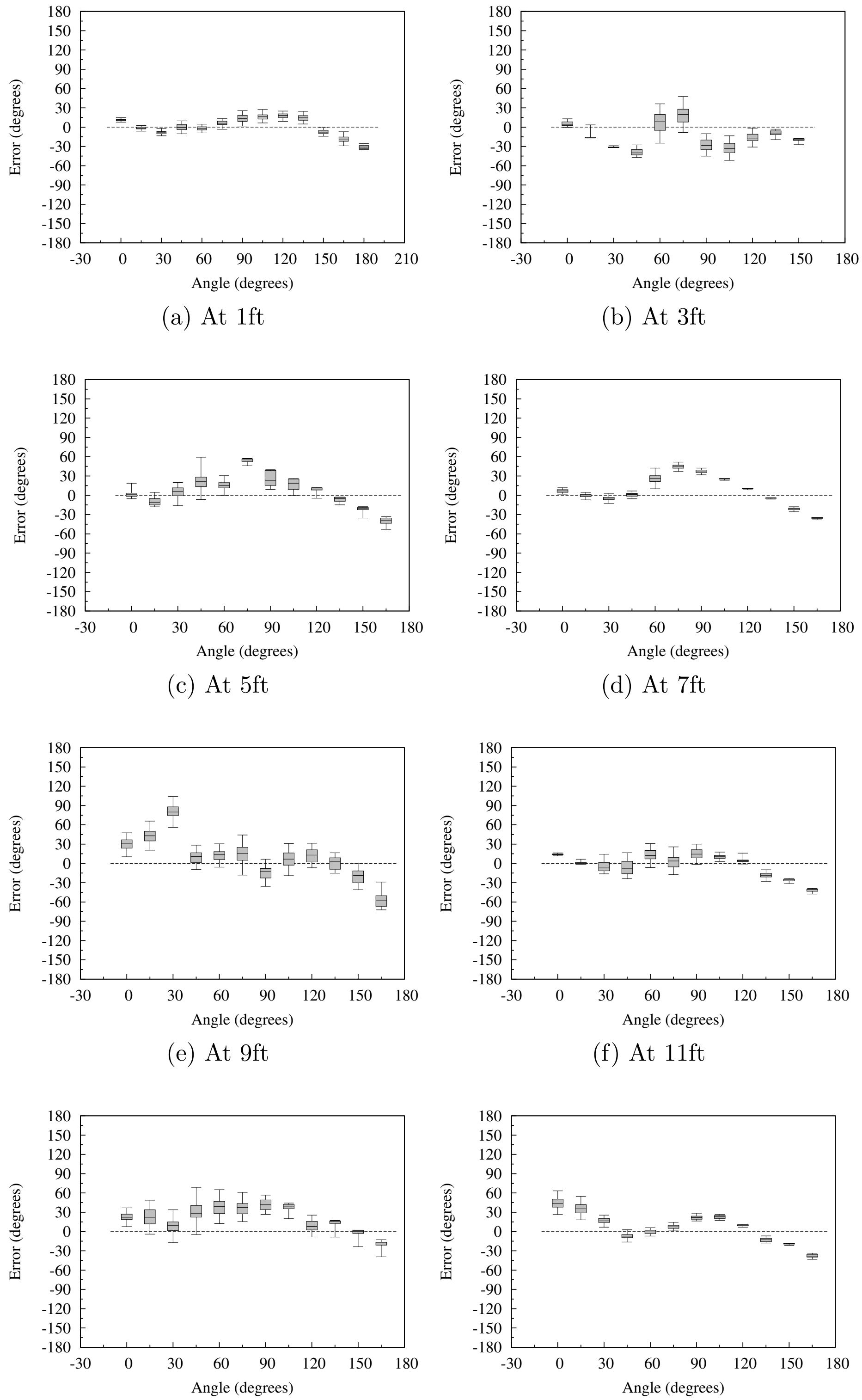


(g) At 13ft



(h) At 15ft

Figure 4.6: 3-Samples Combined Angle Error



(a) At 1ft (b) At 3ft

(c) At 5ft (d) At 7ft

(e) At 9ft (f) At 11ft

(g) At 13ft (h) At 15ft

Figure 4.7: 10-Samples Combined Angle Error

CHAPTER 5

CONCLUSION AND FUTURE DIRECTIONS

This thesis seeks to shed light on a new dimension of context-based computing enabled by angle estimation. The feasibility of using directional antennas as a measurement sensor was shown through real world data collection. Finally, the effect of distance error on angle measurements was shown to be minimal if enough samples are taken.

Work remains to deliver this new context to off-the-shelf devices. The lack of directional antennas remains the biggest hurdle to using radio-based angle estimation. One possible direction might be to use the human body as a reflector for a low powered radio, where a high powered radio might be unaffected.

One reason the area of radio-based distance estimation has struggled to reach deployment is the need for calibration. Using relative estimation is an important step to avoiding this setup cost, but more work needs to be done to make distance estimation calibration-free.

Finally, the application space for this technology has yet to be explored. Just now applications are starting to use context and within contextual computing it is the applications which drive the systems. Orientation estimation needs the "killer" application to drive its adaptation.

REFERENCES

[1] M. Kjærgaard, J. Langdal, T. Godsk, and T. Toftkjær, "Entracked: energy-efficient robust position tracking for mobile devices," in *Proceedings of the 7th international conference on Mobile systems, applications, and services.* ACM, 2009, pp. 221–234.

[2] T. He, C. Huang, B. Blum, J. Stankovic, and T. Abdelzaher, "Range-free localization schemes for large scale sensor networks," in *Proceedings of the 9th annual international conference on Mobile computing and networking.* ACM, 2003, pp. 81–95.

[3] N. Bulusu, J. Heidemann, and D. Estrin, "GPS-less low-cost outdoor localization for very small devices," *IEEE personal communications*, vol. 7, no. 5, pp. 28–34, 2000.

[4] N. Bulusu, J. Heidemann, D. Estrin, and T. Tran, "Self-configuring localization systems: Design and experimental evaluation," *ACM Transactions on Embedded Computing Systems (TECS)*, vol. 3, no. 1, pp. 24–60, 2004.

[5] L. Doherty and L. El Ghaoui, "Convex position estimation in wireless sensor networks," in *INFOCOM 2001. Twentieth Annual Joint Conference of the IEEE Computer and Communications Societies. Proceedings. IEEE*, vol. 3. IEEE, 2002, pp. 1655–1663.

[6] P. Bahl and V. Padmanabhan, "RADAR: An in-building RF-based user location and tracking system," in *INFOCOM 2000. Nineteenth Annual Joint Conference of the IEEE Computer and Communications Societies. Proceedings. IEEE*, vol. 2. Ieee, 2002, pp. 775–784.

[7] K. Whitehouse, C. Karlof, and D. Culler, "A practical evaluation of radio signal strength for ranging-based localization," *ACM SIGMOBILE Mobile Computing and Communications Review*, vol. 11, no. 1, pp. 41–52, 2007.

[8] A. Ladd, K. Bekris, A. Rudys, L. Kavraki, and D. Wallach, "Robotics-based location sensing using wireless ethernet," *Wireless Networks*, vol. 11, no. 1-2, pp. 189–204, 2005.

[9] A. LaMarca and E. de Lara, “Location systems: An introduction to the technology behind location awareness,” *Synthesis Lectures on Mobile and Pervasive Computing*, vol. 3, no. 1, pp. 1–122, 2008.

[10] P. Bahl and V. Padmanabhan, “Radar: An in-building rf-based user location and tracking system,” in *INFOCOM 2000. Nineteenth Annual Joint Conference of the IEEE Computer and Communications Societies. Proceedings. IEEE*, vol. 2. Ieee, 2000, pp. 775–784.

[11] A. Haeberlen, E. Flannery, A. Ladd, A. Rudys, D. Wallach, and L. Kavraki, “Practical robust localization over large-scale 802.11 wireless networks,” in *Proceedings of the 10th annual international conference on Mobile computing and networking*. ACM, 2004, pp. 70–84.

[12] M. Bargh and R. De Groote, “Indoor localization based on response rate of bluetooth inquiries,” in *Proceedings of the first ACM international workshop on Mobile entity localization and tracking in GPS-less environments*. ACM, 2008, pp. 49–54.

[13] R. Bruno and F. Delmastro, “Design and analysis of a bluetooth-based indoor localization system,” in *Personal Wireless Communications*. Springer, 2003, pp. 711–725.

[14] A. Hossain and W. Soh, “A comprehensive study of bluetooth signal parameters for localization,” in *Personal, Indoor and Mobile Radio Communications, 2007. PIMRC 2007. IEEE 18th International Symposium on*. Ieee, 2007, pp. 1–5.

[15] M. Sugano, T. Kawazoe, Y. Ohta, and M. Murata, “Indoor localization system using rssi measurement of wireless sensor network based on zigbee standard,” in *Proc. IASTED Int. Conf. WSN*. Citeseer, 2006, pp. 1–6.

[16] J. Blumenthal, R. Grossmann, F. Golatowski, and D. Timmermann, “Weighted centroid localization in zigbee-based sensor networks,” in *Intelligent Signal Processing, 2007. WISP 2007. IEEE International Symposium on*. Ieee, 2007, pp. 1–6.

[17] J. Larranaga, L. Muguira, J. Lopez-Garde, and J. Vazquez, “An environment adaptive zigbee-based indoor positioning algorithm,” in *Indoor Positioning and Indoor Navigation (IPIN), 2010 International Conference on*. IEEE, 2010, pp. 1–8.

[18] R. Stoleru, T. He, and J. Stankovic, “Walking gps: A practical solution for localization in manually deployed wireless sensor networks,” in *Local Computer Networks, 2004. 29th Annual IEEE International Conference on*. IEEE, 2004, pp. 480–489.

[19] K. Laasonen, M. Raento, and H. Toivonen, "Adaptive on-device location recognition," *Pervasive Computing*, pp. 287–304, 2004.

[20] H. Laitinen, J. Lahteenmaki, and T. Nordstrom, "Database correlation method for gsm location," in *Vehicular Technology Conference, 2001. VTC 2001 Spring. IEEE VTS 53rd*, vol. 4. IEEE, 2001, pp. 2504–2508.

[21] A. LaMarca, Y. Chawathe, S. Consolvo, J. Hightower, I. Smith, J. Scott, T. Sohn, J. Howard, J. Hughes, F. Potter et al., "Place lab: Device positioning using radio beacons in the wild," *Pervasive Computing*, pp. 301–306, 2005.

[22] G. Borriello, A. Liu, T. Offer, C. Palistrant, and R. Sharp, "Walrus: wireless acoustic location with room-level resolution using ultrasound," in *Proceedings of the 3rd international conference on Mobile systems, applications, and services*. ACM, 2005, pp. 191–203.

[23] N. Priyantha, A. Chakraborty, and H. Balakrishnan, "The cricket location-support system," in *Proceedings of the 6th annual international conference on Mobile computing and networking*. ACM, 2000, pp. 32–43.

[24] A. Ward, A. Jones, and A. Hopper, "A new location technique for the active office," *Personal Communications, IEEE*, vol. 4, no. 5, pp. 42–47, 1997.

[25] R. Want, A. Hopper, V. Falcao, and J. Gibbons, "The active badge location system," *ACM Transactions on Information Systems (TOIS)*, vol. 10, no. 1, pp. 91–102, 1992.

[26] L. M. Ni, Y. Liu, Y. C. Lau, and A. P. Patil, "Landmarc: indoor location sensing using active rfid," *Wirel. Netw.*, vol. 10, pp. 701–710, November 2004. [Online]. Available: http://dx.doi.org/10.1023/B:WINE.0000044029.06344.dd

[27] M. Bouet and A. Dos Santos, "Rfid tags: Positioning principles and localization techniques," in *Wireless Days, 2008. WD'08. 1st IFIP*. Ieee, 2008, pp. 1–5.

[28] M. Azizyan, I. Constandache, and R. Roy Choudhury, "Surroundsense: mobile phone localization via ambience fingerprinting," in *Proceedings of the 15th annual international conference on Mobile computing and networking*. ACM, 2009, pp. 261–272.

[29] I. Constandache, R. Choudhury, and I. Rhee, "Towards mobile phone localization without war-driving," in *INFOCOM, 2010 Proceedings IEEE*. IEEE, 2010, pp. 1–9.

[30] S. Lanzisera, D. Lin, and K. Pister, "RF time of flight ranging for wireless sensor network localization," in *Intelligent Solutions in Embedded Systems, 2006 International Workshop on.* IEEE, 2007, pp. 1–12.

[31] A. Savvides, C. Han, and M. Strivastava, "Dynamic fine-grained localization in ad-hoc networks of sensors," in *Proceedings of the 7th annual international conference on Mobile computing and networking.* ACM, 2001, pp. 166–179.

[32] X. Cheng, A. Thaeler, G. Xue, and D. Chen, "TPS: A time-based positioning scheme for outdoor wireless sensor networks," in *INFOCOM 2004. Twenty-third AnnualJoint Conference of the IEEE Computer and Communications Societies*, vol. 4. IEEE, 2004, pp. 2685–2696.

[33] A. Harter, A. Hopper, P. Steggles, A. Ward, and P. Webster, "The anatomy of a context-aware application," *Wireless Networks*, vol. 8, no. 2, pp. 187–197, 2002.

[34] H. Chang et al., "Spinning beacons for precise indoor localization," in *Proceedings of the 6th ACM conference on Embedded network sensor systems.* ACM, 2008, pp. 127–140.

[35] D. Niculescu and B. Nath, "Ad hoc positioning system (APS) using AOA," in *INFOCOM 2003. Twenty-Second Annual Joint Conference of the IEEE Computer and Communications. IEEE Societies*, vol. 3. Ieee, 2003, pp. 1734–1743.

[36] P. Corral, E. Pena, R. Garcia, and V. Almenar, "Distance Estimation System based on ZigBee," in *Computational Science and Engineering Workshops, 2008. CSEWORKSHOPS'08. 11th IEEE International Conference on.* IEEE, 2008, pp. 405–411.

[37] S. Fang and T. Lin, "Cooperative multi-radio localization in heterogeneous wireless networks," *Wireless Communications, IEEE Transactions on*, vol. 9, no. 5, pp. 1547–1551, 2010.

[38] N. Banerjee, S. Agarwal, P. Bahl, R. Chandra, A. Wolman, and M. Corner, "Virtual compass: relative positioning to sense mobile social interactions," *Pervasive Computing*, pp. 1–21, 2010.

[39] K. Srinivasan and P. Levis, "Rssi is under appreciated," in *Proceedings of the Third Workshop on Embedded Networked Sensors (EmNets)*, vol. 2006. Citeseer, 2006.

[40] "Nokia Europe - Nokia N900 - Specifications," http://europe.nokia.com/find-products/devices/nokia-n900/specifications.

[41] "Android - Nexus S - Specifications," http://www.android.com/devices/detail/nexus-s.

[42] "iRobot: Education and Research Robots," www.irobot.com/create.