

Localization in wireless sensor networks

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Introduction

Wireless sensor networks (WSNs) are increasingly being utilized to monitor the physical world across a wide variety of applications. Efficient determination of the location (localization) of sensor nodes in WSNs is both important and challenging. Since equipping every node with a Global Positioning System (GPS) receiver has cost and deployment limitations, most localization schemes rely on radio communication from reference points, also called anchors or beacons. In many cases, including ours, these anchors are nodes in the network that already know where they are. These nodes may be the select few that are equipped with a system like GPS or they may be told where they are by the user at set up. The goal of all localization techniques is to derive a satisfactory degree of accuracy out of inconsistent radio communication with minimal power usage. We concentrate on a technique of beacons transmitting at multiple power levels.

In our research we focus on **measurements-based analysis of our methods**. Second, instead of using geometric calculations, we just aggregate and average the coordinates of heard-from beacons to get our location. Third, **we investigate new questions about radio, distance estimators, thresholds and choice of power levels**.

Experiment

In our experiment we looked to determine the **Received Signal Strength Indicator (RSSI)**, **Link Quality Indicator (LQI)** and **Packet Reception Rate (PRR)** values in relation to distance over 10.0m.

To achieve this test we paired two Sun Microsystems **SunSPOT nodes**, each with a **CC2420 radio that is IEEE 802.15.4 compliant**. We then had the anchor beacon broadcast 200 packets for each of the 22 available power levels from -32dBm to 0dBm, while the receiving node recorded the RSSI and LQI for each incoming packet. PRR was then calculated by comparing the number of received packets to the number of packets sent. This test was performed at 0.25m, and was then repeated for every distance 0.25m greater, up to 10.0m.

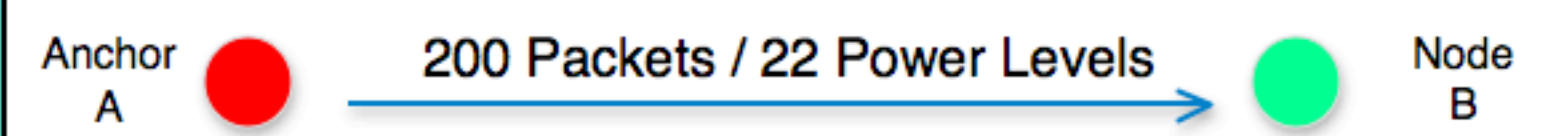


Figure 2. Our experiment was conducted over the course of one afternoon on an artificial turf football field. There were no obstructions on the field during the experiment.

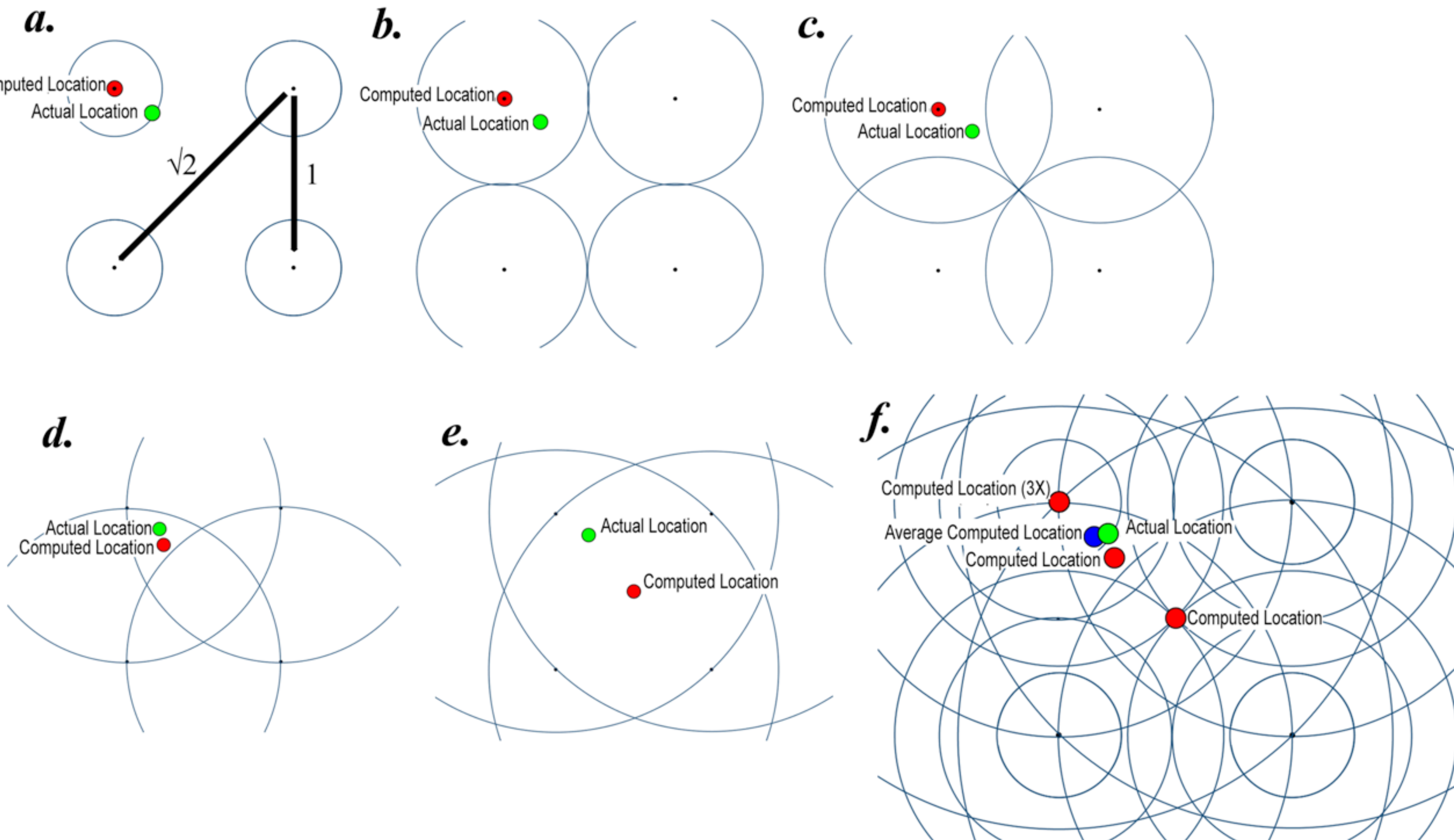
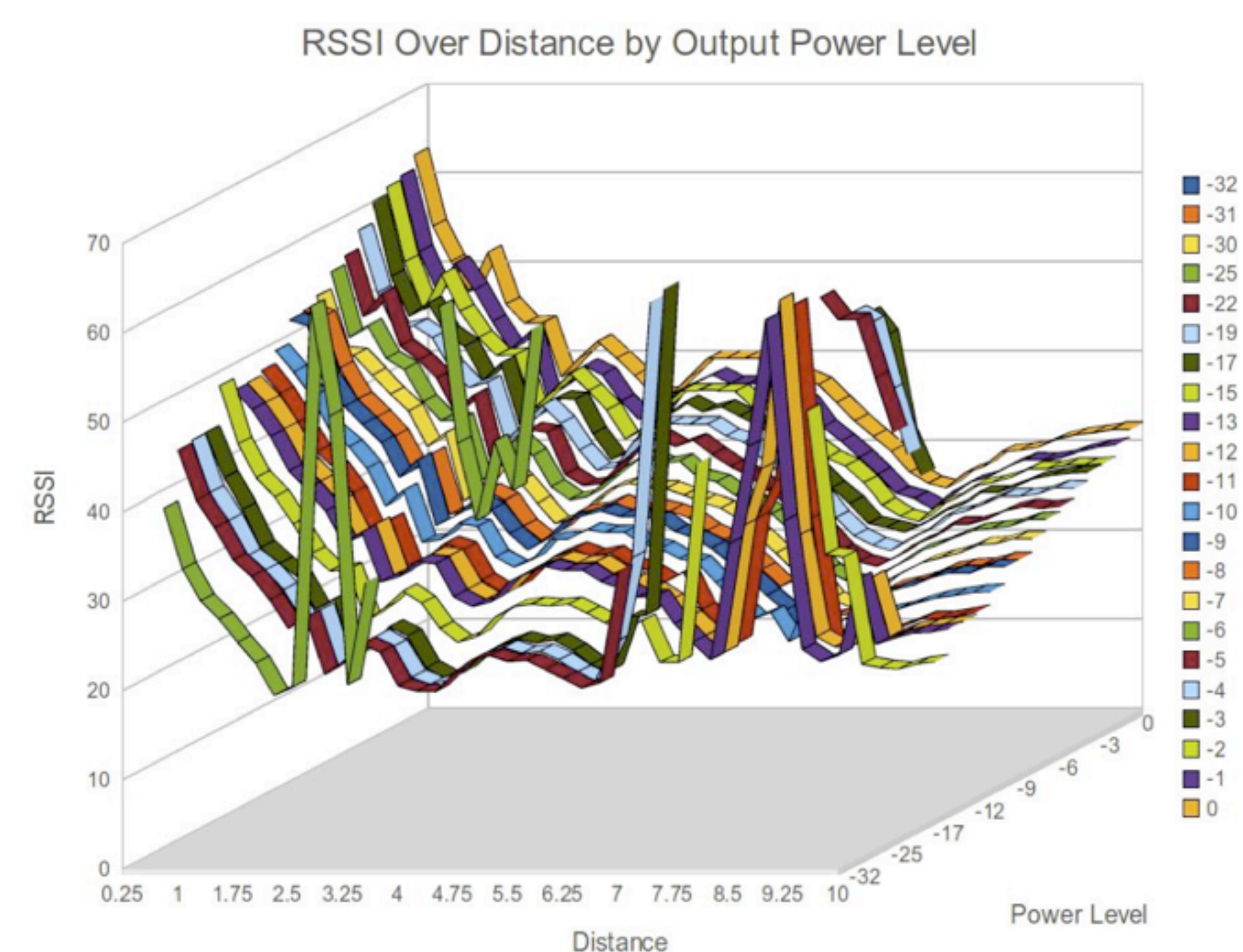


Figure 1. A visualization of **overlapping broadcast regions on a unit square**. Sections a. through e. show the change in overlap as the broadcast radii increase from each beacon (shown as small black dots), along with the actual and computed location of a node within the regions. Section f. shows the same for the **sum of the sections a. through e.**

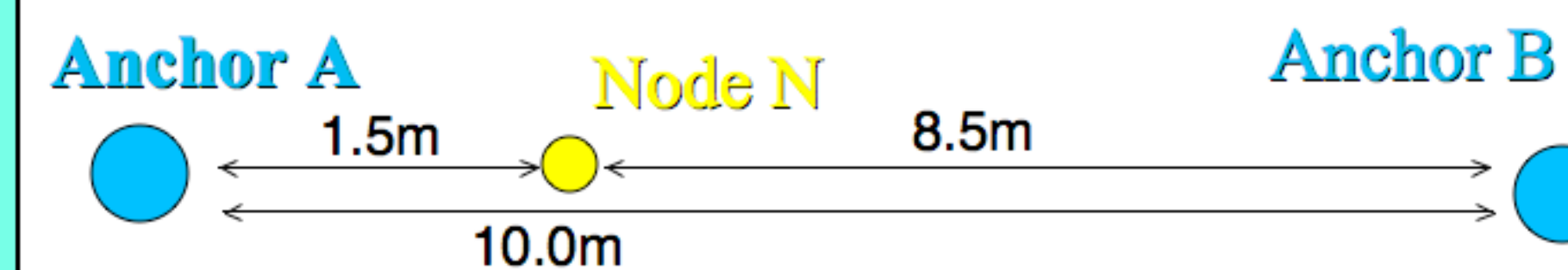
Results

Figure 3. Experimental RSSI data over 10.0m by power level.



Equation 1. This equation takes the data and estimates the position of the node in relation to two beacons. M represents the average of the signal strength metric for A or B. P represents the position of node A, B, or N.

$$((M_B / (M_A + M_B)) \times (P_B - P_A)) + P_A = P_N$$



Model

We took the data from the experiment and paired it with itself. For example the data from 1.25m would be paired with the data from 8.75m. This pairing replicates the data that a node would receive in between **two anchors that are 10.0m apart**.

We realized that maybe there could be some outlier data so we tried to only focus on quality received signals. We were able to do this by only looking at **received signals above a threshold** for that particular metric. This yielded the best location estimates. (See Figure 4) We also attempted to **eliminate some stronger power levels** that were being received from at all distances as we thought they might be skewing our data. This provided some positive results, however, they were not the most reliable.

Sum of the Error Squared by Method Without Power Level Elimination

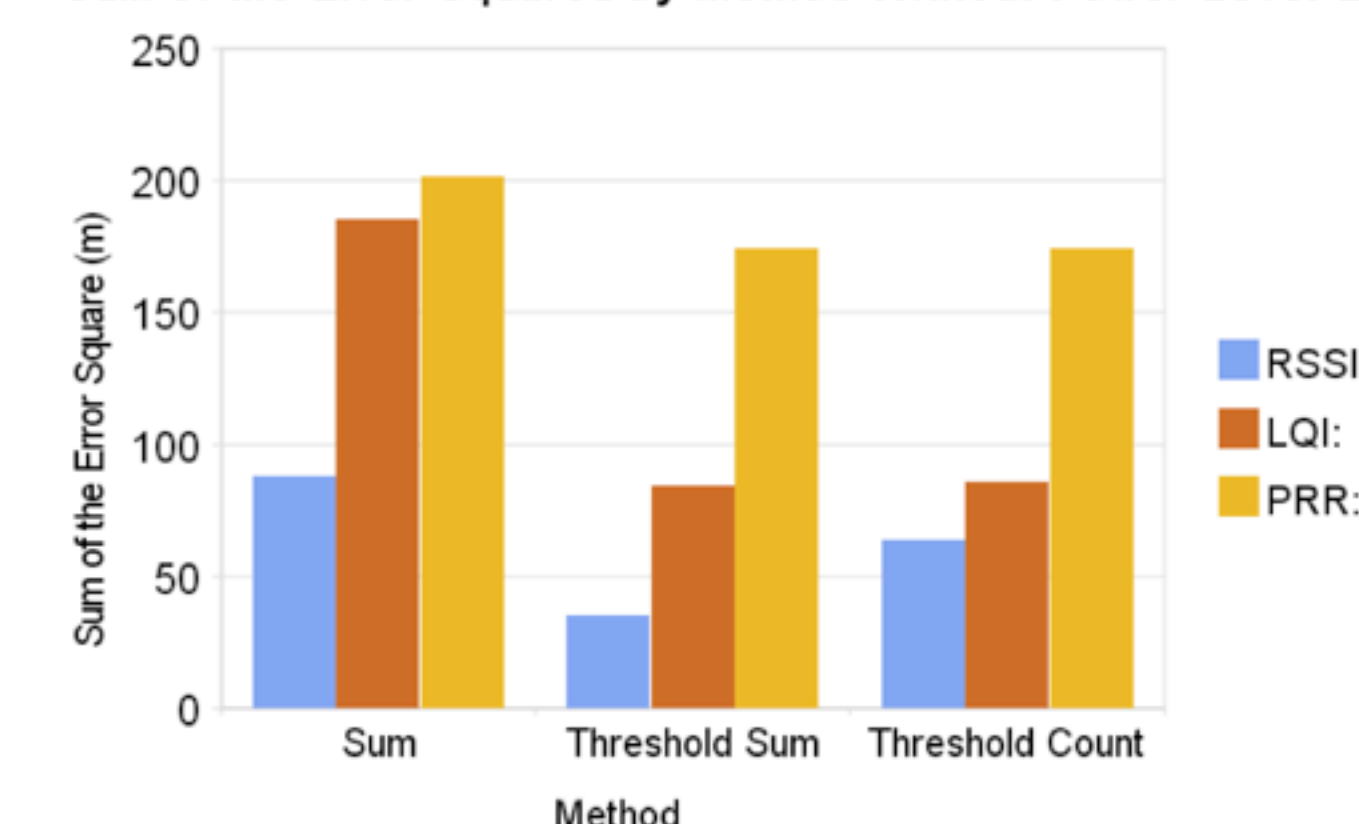


Figure 4. This is the final data for our experiment which yielded the best results. The **overall best localization was with RSSI and a threshold of 24**.

Conclusions

In this research, we extended previous work on localization when anchors broadcast at multiple power levels. Our results show that **RSSI with threshold filtering** and without power level elimination had the **least localization error**. However, in almost all cases (other than RSSI with threshold filtering), power level elimination did reduce localization error.

Localization with anchors transmitting at multiple power levels has merit in several ways. It has the ability to provide finer grained location without additional anchors. The computations are very low-cost. In particular, our **RSSI-based threshold sum method shows promise for both low-cost and low localization error**.

Related Work

The localization method of Bulusu et. Al. was connectivity-based (PRR) and computed the centroid. They experimented with Radiometrix radio packet controllers (model RPC-418) and used a threshold of 90 percent packet reception. Blumenthal et. Al. introduced weighted centroids, where weight is an estimation of distance. They experiment with similar hardware.

- [1] J. Blumenthal, R. Grossmann, F. Glatowski, D. Timmermann, "Weighted Centroid Localization in Zigbee-based Sensor Networks," October 5, 2007. [Online]. Available: <http://www.imd.unirostock.de>. Proceedings of the IEEE International Symposium on Intelligent Signal Processing (WISP '07). [Accessed: June 4, 2010].
- [2] N. Bulusu, J. Heidemann, D. Estrin, "GPS-less Low-Cost Outdoor Localization for Very Small Devices," October 2000. [Online]. Available: <http://lecs.cs.ucla.edu>. IEEE personal communications. [Accessed: June 4, 2010].

For further information

Please contact bperkins@lclark.edu or wwatson@lclark.edu. A copy of this poster, the associated paper, and other information can be obtained from either of these addresses. The paper can also be found in the proceedings of *The 2010 International Conference on Wireless Networks* part of *WorldCOMP '10*, paper #ICW8620.

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