# A Practical Evaluation of Radio Signal Strength for Ranging-based Localization

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*Radio signal strength (RSS) is notorious for being a noisy signal that is difficult to use for ranging-based localization. In this study, we demonstrate that RSS can be used to localize a multi-hop sensor network, and we quantify the effects of various environmental factors on the resulting localization error. We achieve 4.1m error in a 49 node network deployed in a half-football field sized area, demonstrating that RSS localization can be a feasible alternative to solutions like GPS given the right conditions. However, we also show that this result is highly sensitive to subtle environmental factors such as the grass height, radio enclosure, and elevation of the nodes from the ground.*

## I. Introduction

*Ranging-based localization* is the task of identifying the positions of a network of nodes based on estimates of the distances between them, called *range* estimates. In many ways, radio signal strength (RSS) is an ideal modality for range estimation in wireless networks because RSS information can be obtained at no additional cost with each radio message sent and received. The simplicity of RSS is especially appealing for the localization in wireless sensor networks because of their cost, size, and power constraints, despite the fact that RSS may yield very noisy range estimates.

A main challenge with RSS ranging is that the effect of reflecting and attenuating objects in the environment can have much larger effects on RSS than distance, making it difficult to infer distance from RSS without a detailed model of the physical environment. This has given RSS the reputation of being too "unpredictable" for range estimation [9, 29]. Indeed, most RSS-based localization systems use a technique called *RF profiling*, in which the effect of environmental objects such as walls and desks must be mapped out before nodes can be localized, as described in Section II.

It is often assumed, however, that RSS can be used for range estimation in open, outdoor environments that are free from obstructions such as walls and trees. In this study, we empirically characterize the extent to which this is true with a series of both ranging and localization experiments, nearly all of which take place outdoors in an open field. In our ranging experiments, we vary environmental factors such as node elevation from the ground and transmission power while collecting RSS data from a network of 25 nodes, characterizing a total of 51 different environmental combinations. This data allows us to characterize each of these environmental factors in terms of its effect on three different properties of RSS: noise, coefficient of attenuation, and effective range.

In our localization experiments, we perform a sensitivity analysis of RSS-based localization against 35 different combinations of network density and environmental factors. We compare these localization results to those obtained using GPS, which is the most common infrastructure-based solution used to solve the sensor field localization problem. We were able to achieve at best about 4m standard error in location with 49 nodes deployed over half of a football field, indicating that RSS-based localization can be a cheap and effective alternative to GPS for large scale, outdoor sensor network deployments.

However, we also found that RSS-based ranging systems are much more sensitive to environmental factors than expected, even in an "ideal" open, outdoor environment. Changing some environmental factors such as transmission power does not only mean that calibration coefficients must change, but that the radio signal carries fundamentally less distance information and that localization will suffer. This high sensitivity may limit the practical use of RSS for ranging-based localization, even in ideal outdoor environments, unless the system is designed to automatically adjust factors such as transmission power and calibration coefficients.

## II. Related Work

Radios can be used for localization in many different ways. For example, *Range-free* approaches use radio connectivity to ascertain proximity, but do not use RSS and do not estimate actual distances [33]. *RF-profiling* techniques, such as the 802.11-based system described below, rely on RSS for localization but do not use it to estimate distances. These radio-based localization techniques have previously been demonstrated to be effective and several working prototypes already exist. In this paper, we focus on RSS-based, *multi-hop*, *ranging-based* localization, in which nodes use RSS to estimate distances to other nodes and can localize themselves even while being multiple hops from the nearest anchor node. This type of localization is the most suitable for sparse, large-scale sensor networks and has not yet been demonstrated to be an effective technique for sensor field localization.

Most existing systems that do use RSS for localization employ a technique called *RF profiling*, first proposed by RADAR [4]. RF profiling requires a pre-deployment stage in which the RSS of each anchor node is recorded at each position in the two dimensional region to be localized. The readings taken at a particular position can be called the RF profile of that position. At a later time, a node with unknown location matches the RF profile of its current position to the profiles of the positions already recorded. RADAR was able to achieve approximately 4m localization indoors, a result which has been corroborated by several studies using 802.11 [15, 8, 6], VHF [5], cellular radios [28, 3], and most recently low-power wireless sensor networks [18]. This methodology is appealing because it has a small, one-time cost to capture a precise, empirical profile of the entire environment which allows it to cope with walls and other sources of RF noise that are common indoors. Although it uses RSS, RF profiling is not considered a *ranging-based* technique because the RSS readings are never used to estimate distance; they are used to directly estimate the node's location. It is also not *multi-hop* because the mobile nodes must always have direct radio communication with the anchor nodes. Indeed, the main limitation of RF profiling is that it requires pre-collected data and a dense infrastructure of anchor nodes. A recent study has shown that Bayesian inference can achieve similar results without a pre-collected RF profile [19], although this technique does not remove the density requirement.

Most studies that use RSS directly for range estimation have yielded inconclusive or negative results, even outdoors. Indeed, the RF-profiling technique was originally motivated by the fact that RSS ranging indoors was found to be ineffective [4]. One study that explored RSS ranging outdoors in both an open and a heavily wooded environment using two 802.11 nodes, but only promised 50% standard error at best [31]. RSS ranging was shown to be effective for indoor localization to within 1.8m in another study, but only when the nodes had a 2-3 meter spacing and RSSI was measured using the Berkeley Varitronix Fox receiver, a high-fidelity Wi-Fi propagation analyzer [21]. The cheap, low-power-consuming radios that are common in sensor networks are even more difficult to use for ranging. Several studies that characterized RSS data using low power radios decided not to use these radios for multi-hop localization [11, 14] or later rejected RSS in favor of other ranging technologies [25, 35]. Today, for real deployments that require sensor field localization, more costly alternatives to RSS such as acoustic, RF time of flight, or laser are being developed to localize nodes outdoors in open spaces with only 10 or even 2 meter spacing [2, 7, 10, 13, 17, 22, 23, 26, 30]. This reflects a general lack of confidence in RSS ranging in the community, although no conclusive results have definitively shown RSS ranging to be impossible or have identified when RSS ranging is or is not applicable. To our knowledge, this is the first systematic study of RSS that successfully localizes a mid-scale, multi-hop sensor network using ranging-based RSS localization, and that establishes the boundary conditions with which successful localization may be achieved.

## III. Characterizing RSS

The power with which a radio signal is received can be calculated by measuring the voltage on the RSS indicator (RSSI) pin on the Chipcon CC1000 radio and using the following equation [1]:

$$P = -51.3 * RSSI - 49.2[dBm]$$

In this section we define three important characteristics of RSS, each of which has a different effect on overall localization results: noise, the attenuation rate, and the effective range.

*Noise* is the standard deviation $\sigma$ of all RSS values that may be observed at a particular distance in a given environment. Even with a single pair of stationary nodes, RSS will vary to some degree due to ambient noise. Much greater variation can be observed by placing a single pair of nodes in more than one location, due to the effects of changing environmental factors such as trees or walls. Finally, individual radios can vary significantly in both transmission strength and receptivity, especially in cheap, low-power radios [11, 34]. Two different pairs of nodes that are the same distance apart may therefore yield very different RSS readings.

The *attenuation rate* is the rate $\alpha$ at which signal strength decreases over distance: $RSS \propto d^{-\alpha}$. As a rule of thumb, if $\alpha = 2$ then signal strength drops by 3dB every time distance doubles. This sub-linear attenuation rate means that the difference in signal strength between 1m and 2m is similar to the difference between 10m and 20m: exactly 3dB. Taking this into account, a constant level of *noise* can result in ever increasing *error* when signal strength is used to estimate distance; if RSS noise is sufficient that we cannot tell the difference between 1 and 1.5m, we also cannot tell the difference between 10m and 15m. As shown in Figure 1, changes in signal strength due to distance become small relative to noise, even if the level of noise remains the same over distance.

The value $\alpha = 2$ is a theoretical attenuation rate derived from the point-source antenna model which distributes propagated energy over a sphere with surface area $4\pi d^2$. In the real world, however, propagation patterns are non-spherical and environmental sources of attenuation often cause the value $\alpha$ to be greater than 2. Higher values cause the curve $\frac{1}{d^\alpha}$ to level-off much more quickly. Following the logic from above, therefore, higher values correspond to lower resolution in distance in the face of equivalent noise.

*Range* is typically considered to be the maximum distance at which a signal can be measured. However, several studies have shown that the probability of making a range measurement may decrease over distance [35, 36]. We therefore define *effective range* to be the integral over the probability of making a RSS measurement at a particular distance $p(\text{measurement}|d)$ weighted by the probability of finding a neighbor at that distance $\Pi * d^2$:

$$\int_{r=0}^{5} \Pi * d^2 * p(\text{measurement}|d)$$

As shown in several studies, the average number of neighbors in a network, or the average *degree*, has a significant impact on many localization algorithms [35, 16]. Effective range is a measure of the expected degree of a node given the probability of obtaining a range estimate at each distance, independent of node density. By measuring the effect of range on expected node degree instead of measuring the maximum possible range, effective range is more indicative of how range effects localization error than typical range characterization.

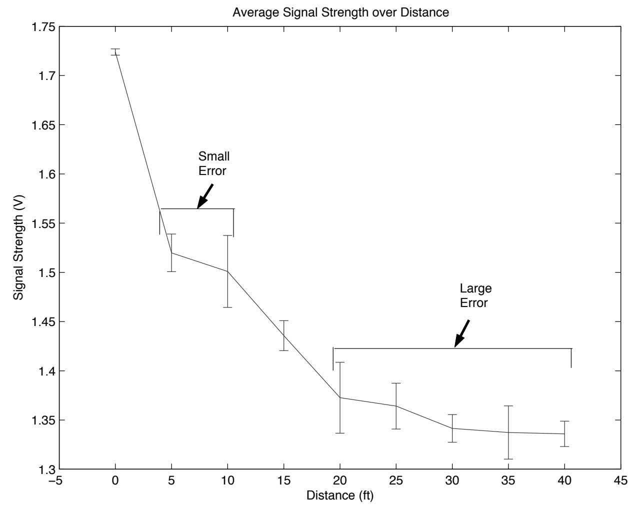



Figure 1: **Error Increase over Distance** *depends on both* noise *and* attenuation rate. *As the signal strength flattens out, differences in signal strength become small relative to noise levels.*

# IV. Ranging Experimental Setup

We designed several experiments to identify the extent to which RSS ranging is affected by various environmental factors. We collected data from 51 slightly different environments and then characterized the data in terms of the three quantities described in Section III. This allows us to quantify the effects of several important environmental influences. However, note that while the influences identified are very significant, most are minor compared to differences due to multipath effects or large attenuating obstacles.

We collected the RSS data in this study using a novel data collection technique that we presented in [35], which uses a specially generated 2D topology of 30 nodes where each pair of nodes in the topology measure a different distance. We deployed the nodes

Figure 2: **Indoor Data** *was collected in a large room with no walls, but some clutter.*

in this topology 5 times for each environment, with a different mapping of nodes to topology positions. For each environment, this procedure collects 330 empirical measurements at every distance between 0 and 30m with a resolution of higher than 30cm, which is approximately the same as the human error in placing the nodes. The 330 readings at each distance are taken with 10 different transmitter/receiver pairs (including reciprocal pairs A/B and B/A) with random antenna orientations. A total of about 7 million range estimates were taken. The exact topology we used and a histogram of the distances that it measures are shown in Figure 3.

We used the mica2 and mica2dot hardware platforms, which have an Atmel Atmega 128 4MHz processor and a Chipcon CC1000 radio. Our mica2dot used a plastic enclosure and large battery that were used in previous tracking experiments [30]. While every radio has its own characteristics, we used the CC1000 because it was the low-power radio shown to be most promising for RSS ranging in previous literature [18].

The following environments were empirically characterized using the data collection process described above. Indoors, in a large 22x12m room that was cluttered with chairs, pillars, and other items, as shown in Figure 2, we characterized the environment 6cm from the ground at five different transmission powers: -20, -15, -10, 0, and 10dBm. The mica2dot node stands at about 6cm off the ground when upright in its plastic enclosure. Outdoors in a field known as West Gate (WG) shown in Figure 5(a), we characterized 3 elevations of 0, 6, and 30cm over a 30x30m area. We used wooden dowels to raise the nodes to the 30cm elevation. At each elevation, we characterized all 5 transmission powers. We also repeated the experiments at 30cm twice, at two different times of day, for a total of 21 different environmental characteristics.

In a different open, grassy field known as Richmond Field Station (RFS), shown in Figure 5(b), the grass was taller and of a different breed with different moisture content. At all five power settings, we characterized only two elevations of 6cm and 30cm because we knew that the 0cm elevation was not interesting, for a new total of 31 characterizations.

In the RFS field, we then characterized two variations of the mica2dot platform's form factor. We first characterized the mica2dot without its plastic enclosure and then characterized the mica2 platform. Both the mica2 and mica2dot use the same Chipcon CC1000 433Mhz radio and Atmel Atmega128 microcontroller. The main difference between these two hardware platforms is the form factor and battery; the mica2dot is the diameter of a quarter dollar and uses a coin cell battery while the mica2 is larger and uses 2 AA batteries. We characterized these different form factors at 6cm and 30cm at all five power settings, making 51 environmental characterizations in total.

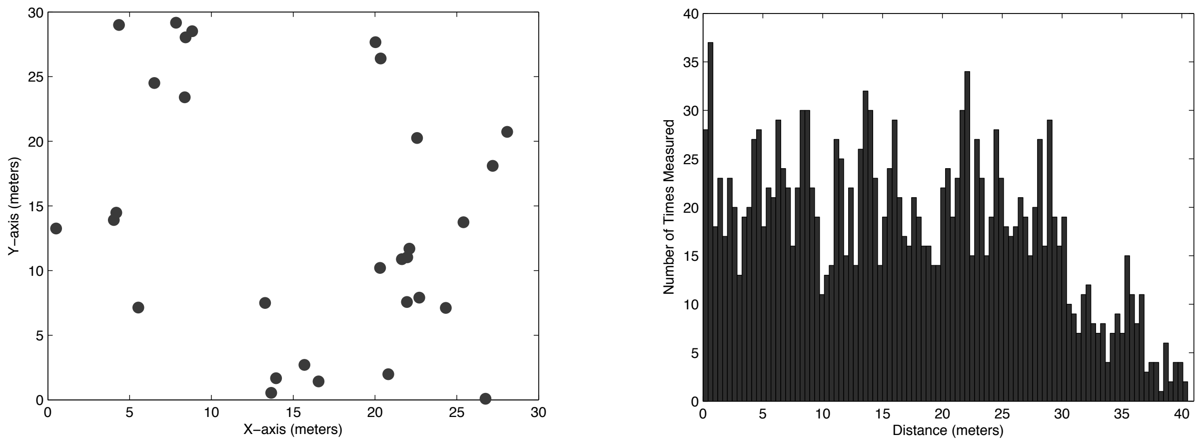
One difference between the WG field and the RFS field, besides the height of the grass, is that the WG field is bordered in the distance by tall trees and buildings while from the RFS field the horizon is generally visible. This difference does not effect RSS, but as we will see it does effect GPS. A rough analysis of each environmental variable measured by the characterizations from Section III is presented below.

## V. Ranging Results

We analyzed the data sets collected in the experiments describe above in terms of the three characteristics defined in Section III. A comparison of the different data sets allowed us to identify the effect on RSS of each environmental factor.

**Time**

We compared the data collected using the same nodes in the same positions at the same transmission power at two different times of day to identify the effects of time on RSS. After averaging the 330 readings for each of the 870 pairs of nodes, we found that the




(a) Data Collection Topology

(b) Distribution of Measured Distances

Figure 3: **Data Collection** *We used the topology in a) to simultaneously measure 435 different distances with an average 30cm resolution over a 30m area. The histogram in b) shows the distribution of distances measured.*

resulting data was almost identical; the difference in readings between experiments for most pairs was in the noise of the ADC. This means that the distribution of RSS readings observed through our data collection process is *stationary*, indicating that we are collecting enough data to generate reliable RSS readings.

**Elevation**

Small changes in elevation, or the distance of the antenna from the ground, have a large influence on RSS characteristics, including noise, attenuation rate, and range. At -15dBm transmission power and 30cm from the ground, RSS has 3.4dBm of noise, an attenuation rate of 3.5 and an effective range of 13.9m. At 6cm, it has 3.8dBm of noise, an attenuation rate of 4.1 and an effective range of 10.4m. Dropping the nodes the remaining few centimeters to 0cm makes an even larger difference, increasing the noise to 7.9dBm, which makes the signal essentially unusable for distance estimation. For frame of reference, the difference from maximum to minimum signal strength is about 17dBm with this radio.

**Vegetation**

Even small differences in vegetation such as the height of grass can have large effects on RSSI. In one field the grass was nearly 30cm tall in places while, at the other, the grass was 6-10cm tall. The shorter grass yielded a reduction in noise of about .5dBm, which is similar to a rise in elevation from 6 to 30cm. More importantly, the attenuation rate was reduced from 3.5 to 2.66.

**Transmission Power**

Increasing transmission power increases range and reduces the attenuation rate, but actually increases noise, perhaps due to greater multi-path effects from features of the grass and ground. For example, increasing the transmission power from -25dBm to 10dBm reduces the attenuation rate to 1.9, which is approximately the theoretical value of 2. While the effective range increases from only 13.9m to well over 50m, the noise level also increases by up to .5dBm. This combination of positive and negative effects makes the most desirable transmission power difficult to determine.

**Packaging**

One of the more surprising results is that the form factor of the node, battery size, and a plastic enclosure around the nodes can have tremendous effects on RSS. Through comparison of the Berkeley mica2dot mote to the mica2 mote [12], which use exactly the same radio and processor, we found that the mica2's noise in its RSS values was sometimes more than 7.5dBm, similar to that seen at 0cm elevation. Similar results were found when the mica2dot was tested without its plastic enclosure, indicating that the plastic dramatically reduced RSS noise, even though the antenna was outside the enclosure.

**Indoor Environment**

Experiments in an indoor environment revealed no discernible pattern in RSS, even in a large room with no walls and at the very lowest transmission power.

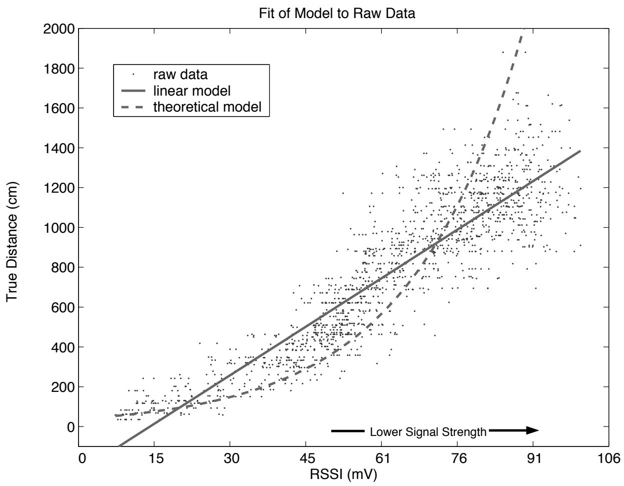



Figure 4: **RSSI Models** *The linear model does not capture the 'dip' near the middle of the curve. However, the theoretical model creates huge errors, especially for the RSSI measurements near 90mV, which are taken near 10m, but are estimated to be 20 or 30m.*

As many people have observed anecdotally, moving two radios farther away from each other indoors does yield predictable attenuation in signal strength. However, in such anecdotal studies, the precise locations of the nodes are being held constant. Our study of indoor signal strength reveals that, without any pre-existing knowledge of the radio's position within a room, signal strength is not correlated to distance. Thus, RF profiling works indoors, but simple ranging does not. However, one promising aspect of our data is that *connectivity* is indeed slightly related to distance, an artifact that will require further study.

## VI. Localization Experimental Setup

In our localization experiments, we use the *DV-distance* algorithm [20], which approximates the distance between a node and an anchor to be the sum of the distances on the shortest path through the network between them. Each anchor initiates a flood where nodes estimate, share, and revise their shortest path distances estimates to the anchor nodes. In this way, the anchor node locations propagate through the entire network, simultaneously building shortest path distance estimates in a distance-vector manner. These shortest path distances are then used for multilateration by each node, essentially reducing the multi-hop localization problem to a single-hop localization problem. APS also uses a *correction factor*, which propagates from the anchor nodes after the distributed shortest path algorithm is complete. The correction factor indicates the ratio of the true distance from that anchor to every other anchor and the distance estimated by the shortest path algorithm. Nodes near to an anchor node can use its correction factor to adjust their own shortest path estimates to other anchors. While APS is only one of many algorithms, we chose it for its simplicity and also because it represents a large class of algorithms that use shortest-path [29, 24, 33] or bounding-box [32, 27] approximations.

Besides ranging errors, there are two new kinds of errors that the shortest-path technique incurs. The first is caused by the fact that any process that finds the shortest-path distance systematically prefers ranging estimates with negative errors. For this reason, multi-hop distance estimates can be much shorter than expected. The second type of error arises from non-convexities in the network, e.g. a *hole* in the network. Since shortest paths must go around this hole, many estimates may be much longer than the true distance.

For each run of the localization algorithm, we use linear regression and uniform linear calibration on all nodes to infer distance from RSS. The regression and calibration coefficients were derived using the maximum likelihood estimator on the ranging data collected in the environmental configuration corresponding to that in which localization was to take place. While RSS has clear non-linearities, linear calibration provides a rough approximation and, as shown in Figure 4, often fits noise better than a theoretical model.

To evaluate the sensitivity of the system, we deployed it in several slightly varying environments. The first deployment was a 49 node network in a 50 x 50m area, the area of half of a football field, at the RFS field. This network at RFS was localized in 10 scenarios: two elevations of 6cm and 30cm, and five transmission powers of -20dBm, -15dBm, -10dBm, 0dBm, and 10dBm. It was then down-sampled twice to 25 nodes and 12 nodes by removing every other node and all ten scenarios were repeated, for a total of 30 scenarios. The last deployment was at the WG field with 25 nodes deployed in a 33 x 33m area because, while the field was quite large, there were no 50 x 50m areas without trees or other obstacles. It was localized at 30cm elevation and all five transmission powers, making a total of 35 scenarios. The topologies were randomly generated using randomly-perturbed grids to fit

(a) West Gate Field

(b) Richmond Field Station

Figure 5: **Outdoor Fields** *The West Gate field had lower grass but was bordered in the distance by tall trees and buildings. The Richmond Field Station was wide open, but with tall grass.*

the number of nodes in the area of the field. True positions were verified with 200ft tape measures and are estimated to be accurate to within 30cm.

To initiate each experiment, the network was flooded with parameters such as transmission power and calibration coefficients. The four nodes in the corners of the network were designated as anchor nodes and were given their true positions. Then, the entire algorithm was started with a single command that was flooded into the network. The entire algorithm ran independently and node locations were calculated in the network without the use of a centralized computer. During each experiment, a laptop would eavesdrop on the network to reveal current progress and, afterward, an automated script would retrieve the resulting range and location estimates from all nodes. The localization system was run 10 times in each of the 35 scenarios and results are averaged over all runs.

## VII. Localization Results

The median error for each of these 35 deployments is depicted in Figure 6. The best results were achieved in the 49 node RFS deployment at transmission power of -10dBm, which yielded a median density of 4.1m and a 95th error percentile of 8.9m. Reasonable results could be achieved in two other deployment classes with lower densities. For example, with only 12 nodes in the 50 x 50m area and with a higher transmission power, the system yielded a median error of 6.3m and 95th percentile of 23m.

Although some deployments did provide reasonable results, slight variations on the environment could cause these same configurations to fail. For example, when transmission power of the 49 node RFS deployment was reduced by 10dBm, the network failed to localize at all. At 10dBm higher, the errors increased by a factor of two to 8.3m. When the elevation was reduced by only 24cm, the network did not localize at the same transmission power. Instead, when either the elevation or density was lowered, the optimal transmission power needed to be increased by 10dBm. These results indicate that RSS localization can work, but is extremely sensitive to environmental variants. It therefore may not be a practical solution for localization unless the environment is well understood and/or the system is designed to automatically tune parameters such as signal strength and calibration coefficients.

Changing fields from RFS to WG increased median errors from 4.1m to 6.1m, despite the fact that the RSS characteristics at WG were superior. This needs to be further explored, but it is suspected to be due to the fact that, in the deployment, the topology was expanded until it was actually under the trees so that we could fit the deployment on the field, as shown in Figure 5(a). Results of two of the larger deployments are shown in Figures 8 and 9.

### VII.A. Analysis

The deployment results reveal an interesting trend: increasing the *physical* density of the network *de-*

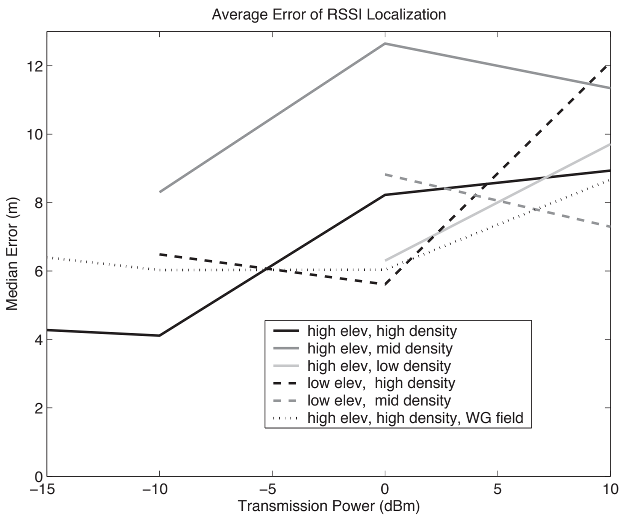



Figure 6: **Median Errors** *This plot depicts the median error for each of 35 deployment scenarios. At points not plotted, the network did not successfully localize.*

*creases* localization error while increasing *communication* density of the network *increases* error. Thus, the best localization should be obtained with many nodes and low transmission power. Closer inspection reveals that this trend is the result of a complex interaction between the algorithms, the precise topology, and the RSS noise characteristics.

The linear RSSI model illustrated in Figure 4 overestimates mid-distances and underestimates long distances. Increasing the communication density of a network will therefore increase the number of underestimated distances more than the number of over estimated distance. This property interacts badly with the APS shortest path algorithm: increasing transmission power both *straightens* the shortest paths because links are longer and *shortens* them because more links are underestimated. This combination quickly overshortens the shortest paths as transmission power is raised.

Because of the small size of this particular topology, high communication density also causes problems with the correction factor algorithm. The correction factor algorithm works on the assumption that, if anchor $A$ and its neighbor $B$ are several hops from anchor $C$, both shortest paths to $C$ probably share several hops in common and therefore have correlated errors. However, with high communication density, a network of this small physical size can be almost entirely connected, making the correlation of shortest path errors between an anchor and its neighbors very limited. Thus, at high densities correction factors were seen to actually increase error.

Given these trends, one might think that lowering the nodes to the ground or introducing attenuating vegetation would actually improve localization error because it reduces communication density. However, this was also not true. The effect of each environmental variable is complex, effecting range, noise, and attenuation rate in different ways. Moving nodes closer together, however, allows the nodes to remain sufficiently connected with fewer obstructions at lower transmission powers, which tend to have low noise. Therefore, our most promising deployment for this algorithm and with this type of RSS noise is a physically dense network with low transmission power and high elevation.

## VIII. GPS Comparison

GPS is often thought to be equally applicable everywhere outdoors and to provide median errors of a meter or two, but we found this not to be the case. GPS coordinates of all node locations were obtained using a handheld Garmin eTrex Legend GPS receiver with Wide Area Augmentation System (WAAS) capabilities enabled. With WAAS, which is a publicly available system that provides GPS corrections, this device is specified by Garmin to have a 95th error percentile of 3m. The localization procedure was to approach each node, wait for the position estimate to stabilize, have the handheld unit record that position as a *waypoint*, and proceed to the next node.

Each network was measured multiple times and, afterward, all waypoints were downloaded and compared to the known positions. To compare the GPS readings with the arbitrary coordinate system defined by our tape measures, we first converted the GPS coordinates to UTM so that they would be in units of meters and then solved for a best-fit linear conformal transform, which allows *shifts*, *rotations*, and *scaling*, according to the following equations

$$\begin{aligned} X_{tape} &= \beta X_{GPS} \cos\alpha + \beta Y_{GPS} \sin\alpha + T_x \\ Y_{tape} &= \beta X_{GPS} \sin\alpha + \beta Y_{GPS} \cos\alpha + T_y \end{aligned} \tag{1}$$

where $\alpha$ is the angle of rotation, $\beta$ is the scaling factor, and $T$ is the translation in each axis. We also added the ability to *flip* the coordinate system by negating the $Y$ axis if it improved the match. By finding the best possible transform between the GPS coordinates and the true coordinates, we gave GPS the benefit of the doubt that it has *no* bias or skew, even though this is unlikely to be true. If there was any bias or skew, it was removed by this procedure giving GPS an advantage over our RSS localization results.

With the 49 node network on the RFS field, GPS yielded a median error of 1.9m error and the 95th error percentile was 7.2m. With the 25 node network on the WG field, the process yielded a median error of 4.2m and the 95th error percentile was 12.6m. These latter results are slightly worse than the RSS localization results obtained at the RFS field, and slightly better that those obtained at the WG field. Sample results are shown in Figures 8 and 9. The first important observation here is that, even in a wide open field, neither deployment met the Garmin specification of a 3m 95th percentile error, even though there were up to two WAAS signals available at times in both fields. The second observation is that there was a dramatic discrepancy from one field to the other. This is due to the number of satellites on which the GPS receiver could acquire lock. At the RFS field, the receiver could often acquire lock on 7 or 8 GPS satellites. At the WG field, however, it would usually acquire lock on only 3 or 4.

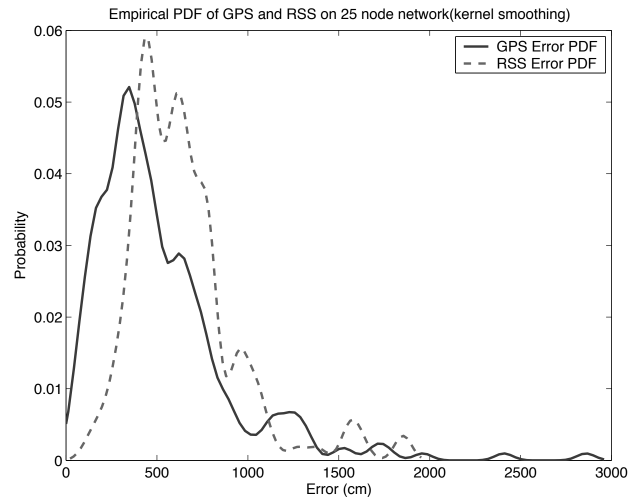



Figure 7: **Error PDFs** *GPS has lower mean error, but has outliers of up to 30m. RSS has a slightly higher average error, but smaller magnitude outliers.*

## IX. Metrics and Comparison

It is difficult to identify a single metric to properly characterize localization error. For example, in the 49 node network on a 50 x 50m field, the 4.1m observed error is less than 50% error relative to the average node spacing and less than 10% error relative to the length of the field. Relative to *area*, the average node was identified to be inside a region that was $0.7\%$ the area of the $2500m^2$ field. In comparison, the 6.3m observed error on the 12 node network fares better with respect to some of these metrics and worse with respect to others. The remainder of this section discusses four different metrics to compare RSS with GPS: an application specific metric, cost of deployment, breadth of applicability, and degree of control.

### IX.A. Breadth of Applicability

One important limitation of RSS localization is the narrowness of applicability. This means that if the environment turns out to be different than expected or changes unpredictably, RSS localization as implemented in this paper may not be effective. Narrowness of applicability, however, is not unique to RSS localization; GPS is only effective when three or more GPS satellites are in clear view. In fact, one reason why GPS performed badly at the WG field is because it was directly bordered at two corners by tall trees. Bordering the field on one side was the city of Berkeley, with two 6- or 7-story buildings a few hundred meters away. On the other side was the UC Berkeley campus, with tall Eucalyptus trees blocking the horizon. These environmental factors have little or no impact on RSS localization, but greatly reduce the effectiveness of GPS; GPS and RSS localization may have at least partly complimentary applicability.

### IX.B. Deployment Cost

With a human experimenter localizing each node, the deployment time for GPS to localize 49 nodes was on average 15 minutes. In contrast, the post-deployment cost for RSS localization was on average 4 minutes and was a completely automated process that did not require a human experimenter. The deployment time of GPS localization could be traded for hardware costs by adding a GPS module to each node, but in either case GPS is disadvantageous in terms of deployment cost, which may outweigh the small accuracy advantages for certain deployment scenarios.

### IX.C. Application Specific Metrics

Localization error can sometimes be accurately characterized only with respect to a specific goal or application. For example, the error pdf of both GPS and RSS localization error from the WG deployment is shown in Figure 7. GPS has a lower median error but can also have extremely erroneous results whereas RSS has higher average errors with fewer extreme errors. Which one is more desirable is a function of the application that uses the locations.

For example, one application that requires location is tracking. As an object moves, the sensor field can estimate its position to be approximately at the center of those nodes that sense it. Because several nodes will sense the object, tracking error would be slightly robust to isolated localization errors but sensitive to more general biases in the network.

### IX.D. Node-level Resolution

The spatial frequency of a phenomenon, or how quickly it changes over space, often determines both the node spacing of the network that is sensing it and its required localization accuracy. Monitoring a phenomenon of low spatial frequency requires a sparse network with low localization accuracy, and vice versa. This *node-level resolution* can often be a desirable feature in spatial monitoring and is one advantage of ad-hoc localization systems over infrastructure-based systems such as GPS. While the user cannot get GPS to yield lower than a 95th percentile error of 3m without deploying a DGPS base station, increasing the physical density of a sensor network both increases its sensing frequency and its ability to localize.

## X. Conclusions

In this study, we demonstrate that radio signal strength with low power radios can be used for direct distance estimation in an ideal open, outdoor environment. Furthermore, we define three metrics with which to characterize RSS and perform a sensitivity analysis of these metrics to different environmental factors. This analysis reveals that, even in ideal environments, RSS ranging is not straightforward; subtleties such as 6cm of elevation or 20cm of extra grass on the field have a significant impact.

We combine RSS ranging with a very simple localization system to achieve near GPS-level accuracy on a half football field with 49 nodes. This positive result is intentionally coupled with a large number of localization failures: we know how applicable RSS-based localization is only when we know where it succeeds and where it fails. These failures helped to illustrate, for example, how the APS algorithm is vulnerable to several properties of high transmission power.

In conclusion, RSS-based ranging and localization can be cheap and effective alternatives to the higher costs or complexity involved with other localization techniques such as GPS, but only when applied in the right environment. This not only means that the nodes must be elevated from the ground and free from obstructions, but also that the transmission power must be appropriate given the algorithm and the node density. Due to these very strict constraints, RSS localization has limited applicability in unknown or changing environments, unless the system can be made to automatically adjust parameters such as signal strength and calibration coefficients.

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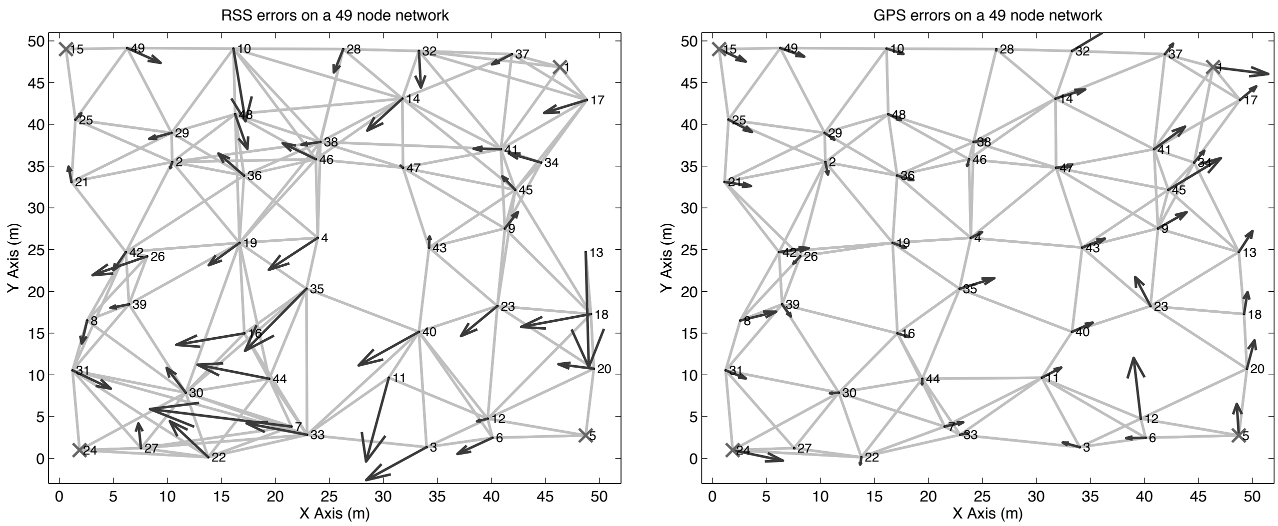


Figure 8: **49 Node network** *"***X***"'s indicate anchor nodes, dots are mobile nodes, and arrows indicate localization errors. Edges in the left graph indicate radio connectivity, in the right graph they indicate distances of 15m or less. RSS localization (left) is coping with a connectivity hole in the center of the network. GPS localization (right) does quite well.*

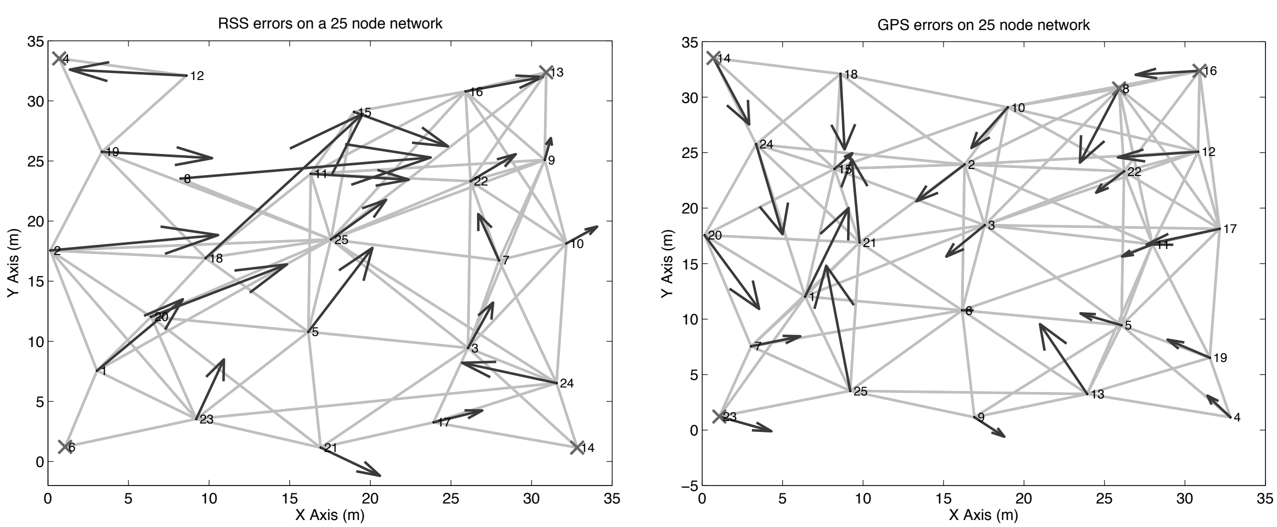


Figure 9: **25 Node network** *Edges in the left graph indicate radio connectivity, in the right graph they indicate distances of 10m or less. In the 25 node network, RSS localization (left) performs well except in the face of connectivity holes (top left corner). GPS has problems with surrounding buildings and trees, which do not effect RSS.*

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