Experimental Analysis of RSSI-based Location Estimation in Wireless Sensor Networks

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***Abstract*—With a widespread increase in the number of mobile wireless systems and applications, the need for location aware services has risen at a very high pace in the last few years. Much research has been done for the development of new models for location aware systems, but most of it has primarily used the support of 802.11 wireless networks. Less work has been done towards an exhaustive error analysis of the underlying theories and models, especially in an indoor environment using a wireless sensor network. We present a thorough analysis of the Radio Signal Strength (RSS) model for distance estimation in wireless sensor networks through an empirical quantification of error metrics. Further on the basis of this experimental analysis, we implement a k - nearest signal space neighbor match algorithm for location estimation, and evaluate some crucial control parameters using which this technique can be adapted to different cases and scenarios, to achieve finer and more precise location estimates.**

I. Introduction

With a widespread increase in the deployment of mobile wireless systems and applications, the need for location aware services has increased manifold. This is attributed to the application of these services in various spheres of life. Examples of such applications range from navigational systems in a building for guiding a user to his destination, to object tracking systems and many more.

While much research has been done for the development of location aware systems and service architectures in various areas including wireless sensor networks, less attention has been paid towards an exhaustive error analysis of the underlying theories and models, especially in indoor environments. Some of the earlier efforts along similar lines for RF-based user location estimation, are however directed towards the use of 802.11 wireless networks [2]. Another category of work has addressed the problem in the context of infrared (IR) wireless networks, but they suffer from major limitations of limited range and directionality.

In this work, we have not focused on developing another sophisticated location estimation technique for Wireless Sensor Networks (WSN), but our real motivation is to implement a simple localization scheme which is instead based on a strong experimental analysis of Radio Signal Strength (RSS) as a distance measurement technique in WSNs over the 433 MHz wireless channel. On the basis of this empirical analysis, we further work out certain crucial control parameters for the k - nearest signal space neighbor match algorithm for location estimation, which we can adapt to different cases and scenarios, to achieve finer and more precise estimates.

The remainder of the paper is organized as follows. In section 2, we present the related work - discussing the various location estimation systems based on different underlying schemes such as ultrasound sensing, 802.11 wireless networks, infrared sensing and other in WSNs. In section 3, we formally define RSSI and its theoretical model, then explain the significance of the various error cost metrics used for our first category of calibration based empirical analysis. We describe our research methodology and the experimental setups along with the implementation details and the system architecture. It is followed by a description of k - nearest signal space neighbor match algorithm for estimating the location of a target sensor mote. Section 4 forms the core of the paper, where we present and discuss our results and analysis. Finally we conclude with a short summary of our results and future research directions.

II. Related Work

In recent past, many systems have tried to solve the problem of location estimation and object tracking using different models in wireless networks. In this section, we briefly describe some of the major approaches.

The Active Badge System [12], based on an infrared model, is the oldest yet one of the most famous localization system. A badge is worn by a user in the system which emits a unique infrared signal every 10 seconds. This emission is made on an on-demand basis as the sensors placed at different locations pick up the identifiers and relay this information to a central server. Although this system provides a fairly accurate location estimate, it suffers from some major drawbacks such as limited range of infrared sensors and usage of diffused infrared for location estimation which could generate wrong estimates in fluorescent lighting or direct sunlight.

Technological alternatives for infrared based sensing came up with the usage of angle of arrival (AOA) and time difference of arrival (TDOA) techniques. While these systems work effectively in outdoor environments, they suffer from the limitations of multiple reflections of RF and sound signals in indoor environments.

One of the earliest location estimation systems in the area of WSNs is the Cricket indoor location support system [11] developed at MIT, which uses ultrasound transmitters and embedded receivers in the objects being located. It uses RF signals for time synchronization and delineation of the time during which the receiver considers the sound waves it receives. It is based on a decentralized system of sensors, but this causes a huge burden on the tiny power-constrained mobile receivers due to distributed computation and processing of ultrasound pulses and RF data.

Another category of location estimation systems are based on Global Positioning System (GPS) [5]. These systems work extremely well in outdoor environments, but fail to work indoors as the buildings block the GPS signals.

Another class of localization systems which have gained recent popularity are based on radio-frequency (RF). These systems work in two phases, first is the radio map building phase which is done offline. This is followed by the online location estimation in the second phase. The major advantage of such a system is that it does not require any additional hardware and can be easily deployed.

RADAR was the first RF-based technique for location estimation and user tracking, developed at Microsoft Research [2]. It is primarily based on a 802.11 Wireless LAN for building a single monolithic radio map for the network site and uses a k - nearest neighbor match algorithm for search in signal space. While there is certain similarity in their and our research methodology, both differ in significant ways. Their system (1) is based on an entirely different 802.11-based wireless platform, (2) investigates the accuracy variations on a more limited range of *k* values, (3) works on 2.4 GHz license-free ISM band on which signal interference is much prominent with other wireless devices. These points are also discussed in the next sections.

An enhancement method for location estimation based on RSSI-values and extended Kalman filter, using pre-calibration measurements has been described in [6]. However their system is also supported by a standard wireless local area network over the 2.4 GHz frequency band.

The work described in [1] is also based on localization in a WSN using RSSI as the underlying model. However unlike our approach, which investigates the crucial control parameters for adapting to various scenarios and achieving finer results, their major focus has been to quantify distance estimation errors across multiple environments.

The Cramer-Rao bound (CRB) for location estimation using RSS and TOA relative localization techniques has been derived in [10]. Their testbed developed at Motorola Labs consisted of 12 prototype peer-to-peer wireless sensor devices with RSS measurement capabilities. They conclude that despite the reputation of RSS as a coarse localization model, it can nevertheless achieve an accuracy of about 1 meter RMS in a real testbed environment.

Another category of related work in WSNs, focuses on the evolution of new calibration techniques for optimizing the overall system performance. Calamari, an ad hoc localization system [13] estimates the distance between wireless nodes using RF-based received signal strength and acoustic time of flight (TOF). In this work, they present the trade-offs between the heavy engineering of a system and its heavy calibration. They propose new calibration techniques to solve this problem, instead of adding special hardware or other infrastructure.

Overall system performance largely depends on efficient query processing too. In [7], the major focus is on sophisticated data analysis for vehicle tracking. It is based on the idea of building a framework which can combine intelligent tracking with other ad hoc query facilities using a sensornet query engine such as TinyDB.

In [15], the focus has been to investigate the impact of radio irregularity on the communication performance of WSN nodes. This work also uses MICA2 platform for getting the empirical data with which they establish a radio model for simulation. They also analyze the impact of radio irregularity on MAC and routing protocols in WSNs.

A decentralized approach to RF-based object tracking, named Mote-Track [8] was deployed at Computer Science building of Harvard University. The testbed consisted of 25 beacon nodes and the system uses the radio signal over 16 different frequencies. Other major works which use signal strength for localization include [4], [14]. In 802.15.4 (wireless personalized area networks), an empirical analysis of RSSI has been done using monopole antennaes [9], but with a major focus on analyzing the physical layer network characteristics.

III. Research Methodology

A. RSSI model and error cost metrics

Received Signal Strength Indicator (RSSI) measures the strength of the radio signal received. Usually calibration is required for mapping RSSI to distance values. It is important to note that RSSI does not imply the quality of the signal. RSSI is usually a 8 or 10 bit number, obtained from the physical layer, and is used for tasks such as issuing of Clear to Send (CTS). The number of bits used for RSSI is hardware dependent. The radio on MICA2/MICA2DOT motes provides RSSI on the Analog to Digital Converter (ADC) channel 0 and is available to the software running on the mote as a 10 bit number. Following is the conversion from ADC Counts (10 bits) to RSSI in dBm as described in [3]:

$$V_{RSSI} = V_{batt} \times ADC\_COUNTS/1024$$

$$RSSI(dBm) = -51.3 \times V_{RSSI} - 49.2$$

$$\text{Signal Strength (in dBm)} = x = 10 \times \log_{10}\left(\frac{Power(in\ mW)}{1\ mW}\right)$$

It is important to note that V_{RSSI} ranges between 0 and 1.2 Volts and a higher voltage means lower input signal. Thus RSSI in dBm is a decreasing function of V_{RSSI} in Volts. For simplicity, we assume free space signal propagation and have the following relation for power per square meter. This is expected because if we consider concentric spheres of increasing radius *r* around the antenna, the total power radiated through the sphere remains constant, however the

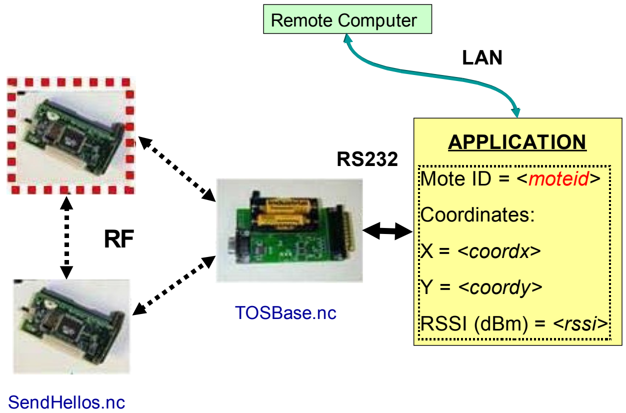

Fig. 1. System architecture.

surface area increases as r^2. This theory also forms the basis of our first experimental setup, discussed later in section III-B.
So, we assume absolute power in milliWatts to be proportional to K/r^2 and that in dBm is defined as the variable x as follows.

$$\begin{aligned} x &= 10 \times \log_{10}\left(\frac{K}{r^2}\right) \\ \therefore,\ x &= 10\log_{10} K - 20\log_{10} r \\ \therefore,\ x &= 10\log_{10} K - 20\log_{10} r \\ &= (-51.3 \times V_{RSSI}) - 49.2 \\ \therefore,\ r &= 10^p \end{aligned}$$

where,

$$p = \frac{(10\log_{10} K + 51.3\,(V_{batt} \times ADC\_COUNTS/1024) + 49.2)}{20}$$

In the above equations,

V_{RSSI}	= RSSI Voltage measured from RSSI/IF pin of CC1000 chip, at the ADC of the μcontroller
V_{batt}	= Mote Battery Voltage
ADC_COUNTS	= 10 bit ADC count at the μcontroller
K	= Constant (Depends on environment)
r	= Transmission Distance

We can observe in the above formulation that transmission distance is an exponential function of the ADC Count value.

The various technologies and schemes used in location estimation in wireless sensor networks suffer from an assortment of errors and dispersions. The foundations for these deviations lie in the very nature of the medium. Noise and interference can hamper the performance of the network because of the losses that they induce. These issues are relatively handled at the physical and MAC layers in the network protocol stack. But in case of distance measurement, noise and optical interference can lead to disastrous results by the induction of

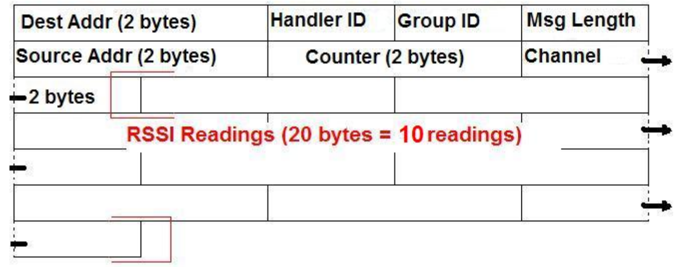

Fig. 2. Packet structure for application.

errors in the distance parameters measured by the devices. Therefore, there is always a need for calibration for location estimation. However, calibration alone can not eliminate the errors completely from the measurements. What is desired is a modeling of the errors in terms of the known (measurable) parameters, so that they can be removed in a fine grained manner. We achieve this by formulating some error cost metrics. In our analysis, we use percentage accuracy as the basic metric which is a measure of the absolute error introduced. It helps us to evaluate the different control parameters in our location estimation algorithm.

B. Experimental Setup

We used the MPR 410 (433 MHz) MICA2 motes which are supplied by Crossbow Technologies, for our experiments. The mote μcontroller has a built-in analog to digital converter which is used to convert a variety of analog signals to digital output, one of them being the output from the RSSI/IF pin of the CC1000 radio chip. The A to D converter, for the signal obtained from the RSSI/IF pin, generates a 10 bit number representing the RSSI for the received signal at the CC1000 Radio Chip.

Our object tracking application (Figure 1) consists of two modules, the sensing module in the wireless domain which comprises of the tracked object, its hardware, software and the underlying protocols. The software consists of a SendHellos application running on the tracked object, which periodically broadcasts HELLO messages every 125 ms, and a base application on the base station(s) which senses the RSSI information for the received HELLO packets and forwards this information, via UART, to a central server for the second module. The second module is the Data Aggregation and Analysis module, or the tracking front end. It consists of the application front end user interface, backend TCP socket interface and a wireless to RS232 interface. Data from the RS232 port is written to a TCP socket, which is henceforth collected by a frontend Java application.

The MAC layer protocol used in our implementation is the default TinyOS version, B-MAC. It is similar to CSMA and is the successor of pre-BMAC version used in older versions of TinyOS. It includes improvements over the earlier version as it employs an adaptive preamble sampling scheme. The data payload of the message which is defined by our application is 26 bytes preceded by the destination address, active message

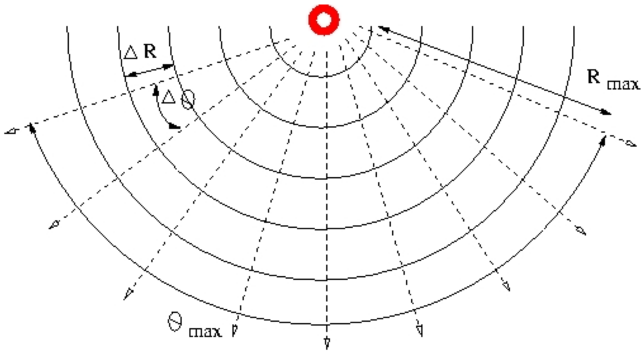

Fig. 3. Calibration equation and basic error analysis setup.

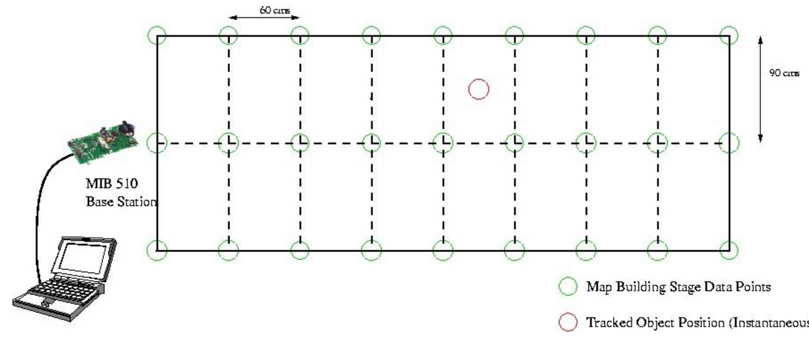

Fig. 4. Setup for location estimation system analysis.

handler id, group id and the message length (Figure 2). This is also the default packet size for B-MAC and is much smaller as compared to other versions of MAC layer protocols in TinyOS. The payload is divided into 4 major fields, first one is source mote id, then the sample counter of two bytes which is followed by the ADC Channel Number and finally there are 10 readings of 2 bytes each, which symbolize the ADC data readings. If we use larger packet sizes then the probability of the packets being delivered decreases due to high memory constraints on the motes, which is not enough for storing a large number of packets for the purpose of link level retransmissions. The data is sent to the motes in little-endian format.

Our experimentation consisted of two stages, which we refer to as setups in the remaining of the paper, the first setup aimed at collection of RSSI data for known distances and angular displacements and generation of calibration equation using this data which also validates our hypothesis that the RSSI value is a logarithmic function of distance from the emitter. This hypothesis is supported by the fact that RSSI (in dBm) is logarithmically related to power of the signal, and power is K/r^2 where K is a constant and r is the distance. Calibration is done using a range of points which are spread over discrete distance values from 0 to R_{max} over ΔR steps. For each distance, data is collected across angular displacements from 0 to Θ_{max} with discrete steps of $\Delta\Theta$. The values for ΔR, R_{max}, $\Delta\Theta$ and Θ_{max} were 25 cms, 700 cms, 15^o and 120^o (Figure 3).

For the second stage (location estimation), we constructed our test-bed in the Department of Computer Science at IIT Delhi. It consisted of a 2 meters $\times$ 7 meters rectangular grid as depicted in the Figure 4. The green circles indicate the points which were used to build the radio map data set during the map building phase of our scheme. The red circle denotes a target mote being tracked in the rectangular field. A MIB 510 board mounted with a MICA2 mote was used to collect the RSSI information of the target mote and forward it to a laptop where the location was estimated, as per the second phase of the scheme. Our primary purpose was to do an exhaustive error and precision analysis for our scheme in an indoor environment, where accuracy and precision for distance estimation using RSSI, are seriously hampered. We also intended to simulate a corridor - like environment in a building where such an indoor tracking application can most likely be deployed.

C. Algorithm and the System

In this section we explain the k-nearest neighbor algorithm and its implementation for location estimation in our system.

1) Radio Map building Phase: For each of the map building stage data points (see Figure 4), RSSI data was collected for 2 minutes (approximately 60000 samples) for two different mote orientations: $+180^o$ and -180^o. Mean RSSI data was computed for each orientation and this data, along with the point coordinates, was stored in our data set Γ. We collected data separately for the two different orientations to observe and analyze the impact of mote orientation on error introduced in estimation.

2) Data Processing and Location Estimation Phase: In our location estimation scheme, we use the k - nearest neighbor algorithm with the following data sets Γ, ξ and χ:

- $\underline{\Gamma}$: The set Γ is built in the initial map building stage, where we profile the area, A, in consideration for location estimation application, by constructing a radio map of the entire area. This is done by collecting the RSSI information for pre-determined locations in the area A, which are well-distributed. In our case, the selection of these points was uniform, lying on the vertices of a planned grid spread out over the area A (see Figure 4). Each element in the set Γ is a 2-tuple $\langle Point\ Coordinates,\ RSSI\ Information\rangle$, which correspond to $\langle Point\ Feature,\ Value\rangle$.
- $\underline{\xi}$: The RSSI information for the tracked mote.
- $\underline{\chi}$: An estimate for the location of the tracked mote. This could be the mean/median/mode of the coordinates from the k nearest matches in Γ to ξ.

K-NEAREST NEIGHBOR MATCH ALGORITHM(Γ, ξ, k)

Find_k_Nearest :
$N \leftarrow size\_of(\Gamma)$
for $i \leftarrow 1$ **to** N
  do $Distance[i] \leftarrow \|\xi.value - \Gamma[i].value\|$
$Sort\_ascending(Distance)$
$k\_Nearest \leftarrow Distance[1:k]$

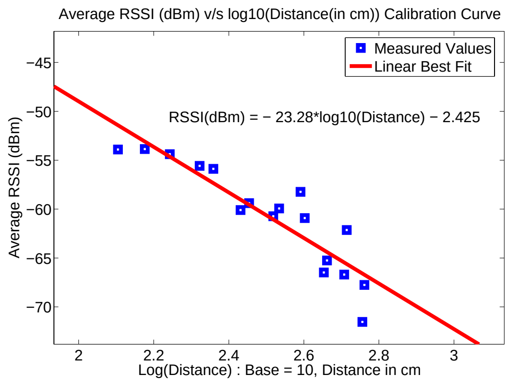

Fig. 5. Calibration curve for RSSI(dBm) v/s $\log_{10}$(Actual Distance).

Estimate_value :
$\chi \leftarrow$ **mean**$(k\_Nearest)$ // *or* **median**, **mode**
return χ

IV. Results and Analysis

In this section, we present an analysis of the results which we obtained in the two stages of our experimentation. First is the *calibration-based error analysis*, where we perform the calibration for the indoor environment. The setup for this was placed in the Advanced Networking Laboratory in our department. The next stage of experimentation is the *fingerprinting-based location estimation*, which uses the k - nearest signal space neighbor match algorithm for location estimation. We assume the target to be stationary in all of the following experiments.

A. Calibration-based error analysis

The experiment for generating the calibration equation, relating RSSI to distance, was conducted to support and corroborate our initial theoretical analysis from which we derived distance as an exponential function of RSSI (in dBm). For this we considered the worst case scenario - indoor environment with large number of obstacles and moving objects. RSSI information was collected for various distances, at various points and for each distance value mean observed RSSI was computed.

The plot in Figure 5 shows the data used for calibration. It was obtained with RSSI(dBm) along y-axis and $\log_{10}$(Actual Distance) along x-axis. The calibration equation and curve were fitted with MATLAB's basic fitting tool. It shows a linear curve fit between RSSI(dBm) and log_{10}(Distance). The linear curve fit gives the following relation between RSSI(dBm) and distance:

$$RSSI(dBm) = -23.28 \times \log_{10}(distance) - 2.425$$

which gives distance as an exponential function of RSSI(dBm):

$$Distance(cm) = 10^{-(\frac{RSSI(dBm)+2.425}{23.28})}$$

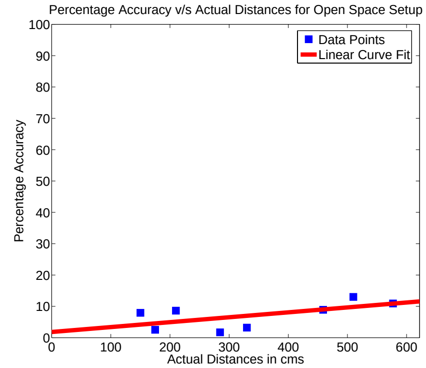

Fig. 6. Percentage accuracy plot - Open Space setup.

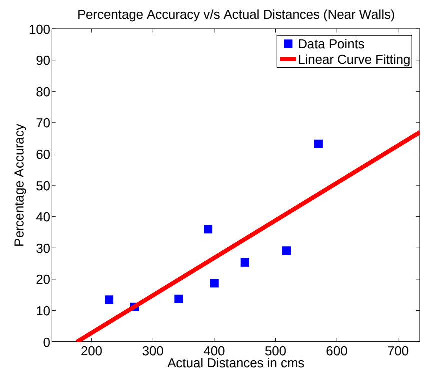

Fig. 7. Percentage accuracy plot - Near Walls setup.

We use this *calibration equation* for computing distances for different known points on our testbed, using which we compute and analyze the error cost metrics.

Here we have demonstrated results for percentage accuracy, which is a measure of relative error in measurements, for two scenarios - (i) in open space (Figure 6) and (ii) near walls (Figure 7). From the graphs we can clearly see that the system produces results for open space with upto 10% accuracy (which is 10% relative error) for 6-7 meters distances. While in case of the scenario where there are obstructions (walls) the error is very large (nearly 60%) for distances upto 6-7 meters. We have only upto 30% error for mediocre distances (4-5 meters). Another important observation that can be made here is the presence of a *zero error* in the latter scenario. This can be attributed to deflection from walls and multi-path fading in this case. This is a significant observation because this zero error can be deducted from the measurements to improve accuracy in estimation. Next, we proceed to using the calibration information for fingerprinting and location estimation.

1) Fingerprinting and Location Estimation: Here we present the analysis of the results obtained for the experimental setup described earlier in section III-B. The k - nearest signal space neighbor algorithm is divided into two phases - *Offline fingerprinting* and the *Online location estimation*. In the first phase, we fingerprint the test environment by building a grid

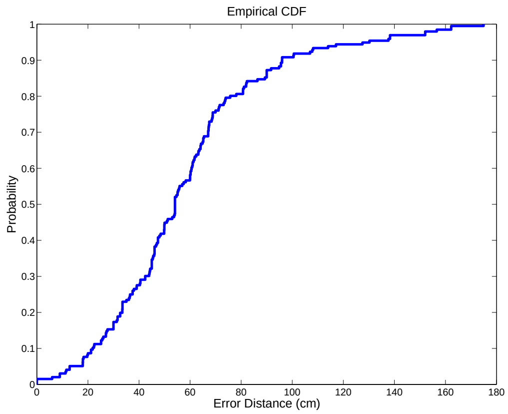

Fig. 8. Cumulative Distribution for error distances.

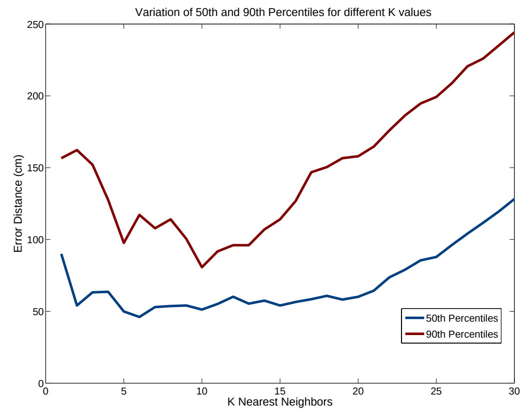

Fig. 9. Variation for error distances with k.

of pre-defined points. We then, find the average RSSI values at each of these gridpoints, thereby generating a radio map of the testbed and maintain this database for the next phase. In the second phase, we collect the signal strength information from the target and find the k - nearest neighbors (the closest values) from the signal space (the data set generated in the first phase), to estimate the region in which the target may lie.

B. Preliminary analysis

We take all the grid-point samples in our signal space and a random location of the target for the initial analysis. Then we run our k - nearest signal space neighbor algorithm and generate a cumulative distribution function (CDF) of the error distances, which is the euclidean distance between the actual and the measured values of the locations. This is made using signal strength samples collected for all the grid points, for certain k values.

Considering the 50^{th} error percentile, our approach has a resolution of nearly half-a meter. Moreover, for 90% of the cases the error distance is under 1.1 meters which is much lower as compared to other RF-based schemes for indoor environments. Hence this CDF (Figure 8) based on empirical results gives a good picture of how robust is the k-nearest neighbor scheme for location estimation in a WSN. We now present how these results depend on some significant control parameters and how can we adapt the scheme to achieve finer results.

C. k - nearest neighbors in signal space

One of the most important evaluation of our location estimation algorithm is to study how its performance varies with the number of candidate neighbors chosen for interpolation in its second phase, that is with the parameter k. Figure 9 represents the variations in the 50^{th} and 90^{th} percentiles of error distances with k.

We observe that as k increases, both the percentiles of error distances initially decrease, then reach an absolute minima and then again rapidly increase. This can be explained as follows. When the value of k increases initially, then the underlying variations of signal strength at the single neighboring grid-points get averaged out with increasing k, resulting in decrease of error distance. Further, to some extent we also believe that the error vectors at the different neighbors of the target mote are oriented in different directions. Hence averaging over more neighbors may yield more accurate estimates of the target's location as these different error vectors nullify each other in most of the cases. However, for larger values of k, the errors again increase as many grid-points which are closer in signal space but much farther in physical space to the target mote, are also included in the data set, thereby leading to greater deviations in measurements from the actual location.

Another observation is that there exists an optimal value of k, which in Figure 9, is in the range of 5 to 10 for both the percentiles at which error distance or the difference between the measured and actual location coordinates is minimum. This result shows that it is empirically possible to infer a set of optimal values for the control parameter k for our algorithm in a given environment and surroundings, which will yield finer and more accurate results.

Similar trends in variation of error distances with k are found irrespective of the orientation of the target relative to the signal space measurements. Figure 10 shows the error variations for three different configurations *up-up, up-down and max(up,down)*. It is important to note that there always exists an optimal control value (OCV) for k at which error can be minimized. However this value or the feasible region for the optimal value is different for each configuration. This is better explained in the next section.

D. Impact of target orientation

The target mote's orientation is an important factor in the estimation of the user location as it significantly affects the signal strength samples received from it. To observe this, we built the radio map in the offline phase with a particular orientation of the motes, which we refer to as *up* and in the online phase we place the target in exactly the same (*up-up* configuration) or 180 degrees opposite to it (*up-down* configuration). Similarly we had *down-up* and *down-down* configurations.

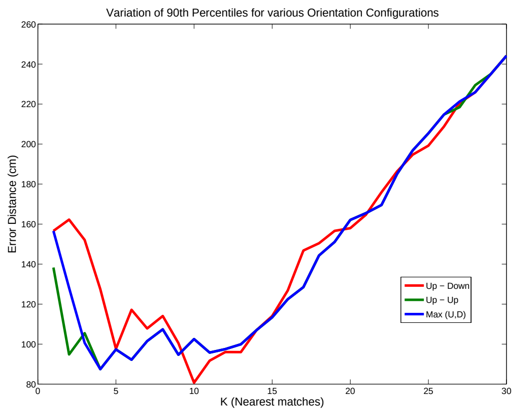

Fig. 10. Variation for error distances for different configurations.

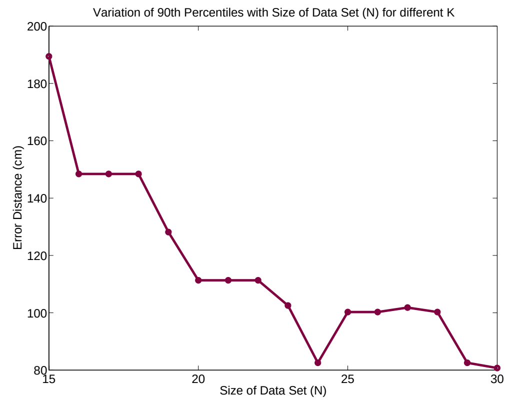

Fig. 11. Variation for error distance for different *N*.

We notice a significant degradation in the accuracy for the *up-down* configuration as compared to the *up-up* one. As in Figure 10, the 90^{th} percentiles of error distance are compared for the three configurations - *up-up*, *up-down* and *max*$\{$*up-down*$\}$. The errors for *up-down* configuration are mostly much higher than that for *up-up* configurations. We can also compare the optimal control values (OCV) for k for the two configurations. The OCV range for *up-up* is nearly for k ranging between 4 and 7, whereas the same for *up-down* configuration is for k from 10 to 13, which is nearly double. Hence, this proves that for achieving the same degree of accuracy in *up-down* configuration, it takes nearly twice the time for computation in the OCV range, as compared to that in *up-up* configuration, as the time complexity for the algorithm is *O(k log(N))*.

We believe that with larger areas of indoor experimentation and with mobile targets, the difference in accuracy levels for the two configurations will increase. Other physical parameters influencing the accuracy levels are mote orientations, antenna directions of both the receiver and the transmitter, and the surface type of the floor between the two motes. Another basis of these variations can be attributed to the RF-based communication phenomena such as multi-path reflections and antenna directionality.

E. Maximal Signal Strength Matching

As we have seen in the previous section, the orientation of the target motes affects the location estimation significantly. We now try to analyze the error distances when we match the observed signal strengths of the target mote with the maximal signal strengths at the grid points. By maximal, we refer to the greatest of the signal strengths among the four possible orientations, namely *up-up*, *up-down*, *down-up* and *down-down*.

Variations of error distances using this strategy, with k is compared with two other configurations in Figure 10. We notice that this strategy certainly reduces the error as compared to the two disjoint configurations *up-down* and *down-up*. The OCV range is also found to be the least for this strategy as compared to the four other configurations. We also observe that this strategy results in lower 90^{th} percentile error distances for even higher values of k. Hence this strategy tries to overcome the effects of physical parameters such as mote orientation and antenna direction, as we now choose one averaged maximal fingerprint of signal strength which is relatively more independent of the mote orientations, for building our offline signal space.

F. Impact of Size of Dataset

We also analyzed how the variation in number of grid points used for the signal space will impact the accuracy of location estimation. To observe this we chose a uniform random distribution of N grid points in our setup. We varied the value of N from 15 to 30 and performed the error analysis for location estimation using k - nearest neighbor algorithm. For each run of N, we used the OCV error distance for our analysis corresponding to the OCV k. Figure 11 shows the 90^{th} percentile OCV error distances for varying N.

We observe a significant improvement in the accuracy levels as N is increased. For smaller values of N such as 15, the error distance is nearly 1.9 meters whereas the same for N being 30 is 80 centimeters. This shows that there is nearly 58% decrease in error distance as N is doubled from 15 to 30. At the same time we also note that this gradient starts smoothening as we increase N beyond a certain value. Hence, we conclude that the accuracy levels in location estimation increase considerably as the size of the dataset is increased but only till a certain threshold is achieved.

V. Conclusion and Future Work

In this work, our major objective has been to quantify how good and accurate is the RSSI model in a wireless sensor network to estimate the location of a cooperative target. We have classified our observations in two broad categories, the first ones are based on a *calibration based analysis* and the second ones are based on a full - fledged scheme for location estimation, the *k - nearest signal space neighbor match algorithm*. Our results are encouraging and we are able to achieve an accuracy of nearly 1.1 meters with 90% probability in indoor environment.

In the first set of results, we quantify the relationship between *relative error* and *actual distance* which we empirically prove to be multiplicative. Once we have a good quantification of the signal strength model, we implemented a location estimation scheme on this basis. The first relationship which comes to surface is the variation of accuracy with changes in the control parameter k. Next we investigated the impact of variation in *mote orientations* on the accuracy of location estimation. Appropriate choice of k within the OCV ranges proved to give more accurate results. Choosing maximal signal strength fingerprints while building the offline signal space, makes the location estimation more independent of user orientation. We also observe that the performance of our system improves as the size of the radio map is enhanced by increasing the number of grid points - N.

One of the extensions to this system built using a WSN could be to analyze how the accuracy levels vary as we increase the number of targets being tracked at the same time from one to more. As we increase the number of motes being tracked, the number of packets being sampled at the base station will increase manifold, which can in turn result in the degradation of sensitivity of the location estimates of the objects.

We would also like to investigate the performance of our system under phenomena such as shadowing and signal contention between different motes and interference with other low-power wireless devices, which work on the same frequency channels.

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