A Systematic Evaluation of RangeQ-based Localization Algorithms in Wireless Sensor Networks

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Abstract: As demonstrated in our previous work, the quantized RSSI based range estimation algorithm (RangeQ) can be used to improve localization accuracy when range information is not available. By converting the signal strength ordering information into a fraction of a unit hop, this technique obtains a more precise hop distance than the DV-hop approach.In order to fully compare the performance of RangeQ-based localization algorithms, we design an experimental framework to evaluate two existing methods and their RangeQ based versions: Ad-hoc Positioning System (APS)and Multidimensional Scaling (MDS)We study several factors that affect the performance of localization, including anchor density, radio range (connectivity), and RSSI error rate. For performance metrics, we use localization variance as precision factor along with the widely-used accuracy factor. To get a better idea of how precise the localization result is, we also compare the whole result set with the Cramer-Rao lower bound of RangeQ.

Key–Words: Localization, RSSI, Evaluation, Wireless Sensor Network

1 Introduction

Recent applications that require instrumenting the physical world and recent advances in MEMS (micro-electro-mechanical systems), embedded systems, processor, radio, and memory technologies have resulted in the emergence of *sensor networks* [10, 3]. These applications, in one form or another, are monitoring either the environment or the natural habitats [1, 7]. Routing, time synchronization, localization, and topology control are areas where new algorithms and protocols need to be developed. The localization problem may be stated as: dynamically determining the physical position in the space of a given sensor node in the ad-hoc wireless sensor network. Formally, the problem may be formulated as follows: Given a connected network of N nodes, where a subset of these nodes $m < N$ (called anchors) know their locations, and given imprecise range measurements among neighboring nodes, find the locations of the remaining $(N - m)$ nodes. This problem definition will be used throughout this paper.

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Current wireless sensor network localization algorithms are categorized either as range-free or range-aware algorithms based on whether they use the range (i.e., distance) information. Although wireless sensor systems usually have available received signal strength (RSSI) readings, this useful information has not been effectively used in the existing localization algorithms. The existing range-free algorithms do not use this information, while the range-aware algorithms require sophisticated ranging techniques to estimate ranges. In RangeQ, we introduce and develop a partial-range-aware localization scheme utilizing RSSI readings. The scheme can be used in any hop-based range-free algorithms to improve their localization accuracy.

In order to evaluate the performance of a localization algorithm, we distinguish two types of metrics: *localization variance* and *localization accuracy*. Localization variance is the precision measurement that tells the degree of reproducibility of the localization result. Accuracy, on the other hand, tells how close the result is against the true position of each node. Most localization studies only consider accuracy as the key performance factor while a few other works show the theoretical aspect of error analysis on variance. Not much work has been done on combining the two metrics to fully present the validity of a localization result set. We design simulations to accommodate both metrics for an in-depth performance analysis.

The accuracy and precision performance metrics are evaluated based on various network parameters. In this paper, we design an experimental systematic evaluation framework to evaluate localization methods for sensor networks. Using this framework, we evaluate two existing localization methods and their RangeQ versions: Ad-hoc Positioning System (APS) [8], localization using multidimensional scaling (MDS) [13], and RSSI quantization based localization (RangeQ). Altogether six algorithms will be evaluated, including APS-HOP (APS range-free), APS (APS range-aware), MDS-HOP (MDS connectivity only), MDS (MDS range-aware), RangeQ-APS (Aps with RangeQ range estimation technique), and RangeQ-MDS (MDS with RangeQ range technique). The network properties that we identify affecting the performance of localization are radius (average network connectivity), range measurement error, and anchor ratio.

The rest of the paper is organized as follows. The next section covers our evaluation framework used to evaluate the localization algorithms. In Sections 3, 3.4, we present the simulation result of localization accuracy and variance, respectively. We conclude our paper in Section 4.

2 Evaluation Framework

In this section, we present an evaluation framework for evaluating the performance of localization methods and our range error model. This framework is applied to three existing localization algorithms: Ad-hoc Positioning System (APS) [8], localization using multidimensional scaling (MDS) [13], and their RangeQ versions. We evaluate their performance on the same platform and simulation setup, as explained below.

2.1 Modeling Range Errors

Sensor nodes in a wireless sensor network communicate through peer-to-peer links, and pair-wise measurements such as RSSI can be made with these links [9]. In RangeQ, we consider S levels of quantized RSSI measurements. The quantized RSSI measurements are subject to the deleterious effects of a fading channel. Received signal strength is attenuated by large-scale path losses, frequency selective fading, and shadowing losses [6, 9].

Let d_{kj} be the true distance between sensor nodes k and j. That is,

$$d_{kj} = \sqrt{(x_k - x_j)^2 + (y_k - y_j)^2} \qquad (1)$$

The received power at device k transmitted by device j (in dBm) can be formulated as

$$P = \Pi_0 - 10 n_p \log \frac{d_{kj}}{\triangle_0} \qquad (2)$$

where Π_0 (dBm) is the received power at the reference distance $\triangle_0$. Typically, $\triangle_0 = 1$ meter, and Π_0 is calculated from the free space loss formula [11]. The path-loss exponent n_p is a function of the environment, typically between 2 and 4.

We assume n_p is a Gaussian random variable, i.e., $n_p \sim N(\alpha, \sigma_{np}^2)$, and the measurement error is Gaussian noise, $N(0, \sigma_{dB}^2)$. The assumption that n_p can be modelled as a Gaussian random variable is supported by a few researchers' work [12, 2, 4, 15]. Based on the data obtained by Seidel et al. [12], the mean of n_p is 3. The measured received power, P_{kj}, at device k transmitted by device j is also a Gaussian random variable

$$P_{kj} \sim N\left(\Pi_0 - 10\alpha \log \frac{d_{kj}}{\triangle_0}, [(10 \log \frac{d_{kj}}{\triangle_0})\sigma_{np}]^2\right) + N\left(0, \sigma_{dB}^2\right) \qquad (3)$$

2.2 Accuracy, Precision, and CRB

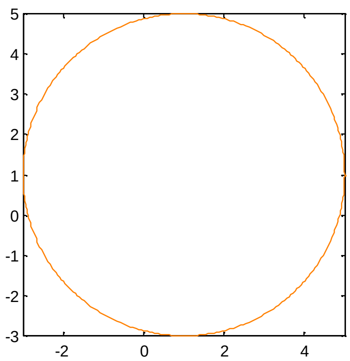
As in many other existing evaluations, the localization accuracy is defined as the difference between a node's real position and its estimated position. A widely-used accuracy representation is the ratio between the mean distance error and the radio range.

The precision is represented by the localization error variance. The localization error variance for the localization algorithms is the mean standard deviation (σ) of the distance between the true position and estimated position of each node. The localization error variance of each network is computed as the mean from the 100 nodes. The final variance is then the mean from the result of a number of networks.

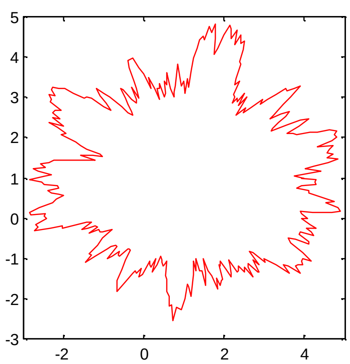
The Cramer-Rao Lower Bound (CRB) is a lower bound on the minimum achievable variances of any unbiased estimates of parameters. The purpose of deriving CRB is to see how well the algorithms perform against each other and the CRB. As formulated in [14], the theoretical variance is the root-mean-squared localization error variance of CRB.

2.3 Simulation Setup

Simulation was done with MATLAB 7.0 on 2-dimensional networks of 100 nodes deployed in a $1000r \times 1000r$ sensing field, where r is the unit length. Instead of a unit-disk approach, we adopt a more realistic model in which the radio propagation pattern is irregular due to path-loss and shading in the surrounding environment. As shown in 1(a), in a unit-disk graph, every node within the disk should be connected to the center node. A more realistic model is a quasi-unit-disk graph [5], where the radio range is a random number which is less than the maximum radius and greater than a minimum distance (See 1(b)).



(a) Unit-disk radio model



(b) Quasi unit-disk radio model

Figure 1: *Radio models*

We conducted several experiments using various combinations of values for three network properties that may affect the performance: average network connectivity (or average degree of a node), ranging error, and anchor percentage ratio. Table 1 summarizes the value(s) used for each property.

The ranging error is considered not only for range-based algorithms, such as the DV-distance version of APS and the range-based version of MDS-MAP. For range-free algorithms, this range error is also effective because of the radio model applied in this investigation. The anchors are randomly deployed with anchor ratios 5% to 20%.

Table 1: *Simulation setup for the evaluation framework*

Parameter	***Range of values***
Number of nodes	100
Sensing field	$1000r \times 1000r$
Radio range	$250r$, $300r$, $350r$
Ranging error	σ_{np}= 0.025,0.035,0.045, 0.065, 0.075,$\sigma_{dB} = 1.3$
Anchor %	$5\% - 20\%$
Range Measurement	Range-based & range-free

3 Simulation Result

In this section, we present the localization accuracy and precision result of MDS-HOP, MDS, APS–HOP, RangeQ-MDS, and RangeQ-Aps. In numbers, accuracy is the mean distance error of the estimated position. So the smaller the error, the more accurate algorithm it is. The evaluation is done on the following three network parameters: network connectivity (radio range), anchor density, and range (RSSI) error rate.

3.1 Localization Accuracy for Different Anchor Densities

Anchor density is an important factor affecting localization accuracy. Higher anchor density has positive influence on accuracy. Figure 2 shows that when anchor density is greater than 10%, the accuracy performance stays flat.

Figure 2 shows that RangeQ-based MDS and APS are more accurate than APS-HOP and MDS-HOP by $20 - 40\%$ of the radio range. By assigning a fraction of the radio range to an otherwise unit-hop value for all 1-hop connections, RangeQ significantly improves the range estimation quality and gives more accurate range value than the DV-hop approach. On the range-aware side, while RangeQ-APS is very close to the range-aware APS, RangeQ-MDS is worse than range-aware MDS by about 10% of the radio range. This tells us that MDS utilizes the available range information better than APS. More discussion can be found in the corresponding variance section.

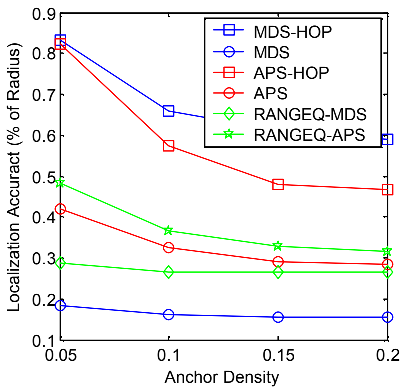


Figure 2: *Improvement of RangeQ over APS-HOP and MDS-HOP: $\sigma_{np} = 0.045$, and radius is 250.*

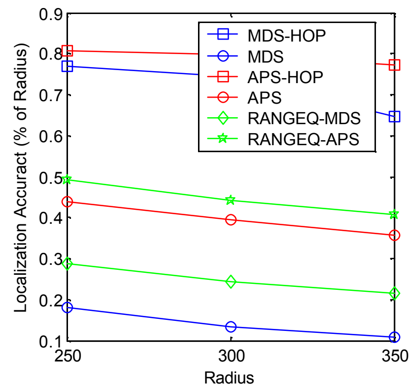


Figure 3: *Localization error accuracy: Anchor ratio is 10%, and σ_{np} is 0.045.*

3.2 Localization Accuracy for Different Radio Connectivity

The accuracy performance ranking for different connectivity is similar among the algorithms compared. Figure 3 shows that RangeQ is $10 - 30\%$ better on localization error variance than the range-free APS and MDS.

One might notice that the improvement made by higher network connectivity shown in Figure 3 is relative to the radio range. The moderate relative gain for greater radio range reveals that absolute position error might stay flat for various radio ranges. This result might be caused by the erroneous radio model. Although increasing radio range provides more range information, it also introduces more erroneous range information since connectivity is not guaranteed in the realistic radio model. Therefore, it is intuitive to assume that there is a minimum connectivity threshold, which gives good-enough localization accuracy and increasing of its value would not improve the localization result. This is an interesting and also important discovery for localization performance tuning and energy saving.

3.3 Localization Accuracy for Different Range Errors (Path-loss Index Errors)

Range error is represented by the path-loss index (exponent) error. Figure 7 shows several interesting "phase" change points. When error rate is less than 0.03, RangeQ-MDS performs worse than APS, but after that, RangeQ-MDS surpasses APS in localization accuracy. At the error rate 0.04, MDS-HOP jumps over APS-HOP with increased position errors after that point. When the error rate is greater than 0.07, RangeQ-MDS is more accurate than range-aware MDS, which shows its less error sensitivity than MDS.

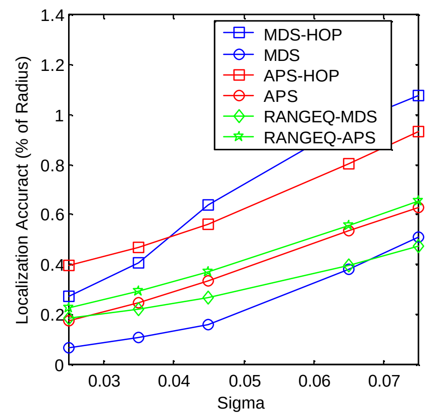


Figure 4: *Localization error accuracy: Anchor ratio is 10%, and communication radius is 250.*

3.4 Localization Precision

Similar to the accuracy result. Higher anchor density has positive influence on variance, too. Figure 5 shows that RangeQ improves the performance of APS-HOP and MDS-HOP by $20 - 40\%$ of the radius. It is not better than the range-aware version of either MDS or APS, but the performance of RangeQ-based MDS and APS is very close to their standalone range-aware versions.This along with the previous accuracy simulation result together shows that the RangeQ range estimation model is valid.

Among all the algorithms, the variance of MDS performs the best. The difference between RangeQ-MDS and MDS is more than the difference between RangeQ-APS and APS, which shows that by using network-wise distance based optimization, MDS utilizes the available distance information more effectively than APS.

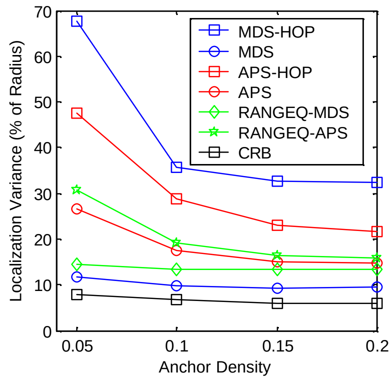


Figure 5: *Improvement of RangeQ over APS-HOP and MDS-HOP: $\sigma_{np} = 0.045$, and radius is 250.*

For connectivity, Figure 6 shows that RangeQ is $10 - 20\%$ better on localization error variance than the range-free APS and MDS. As mentioned in the accuracy section, the effect of radio range on variance is similar as on accuracy.

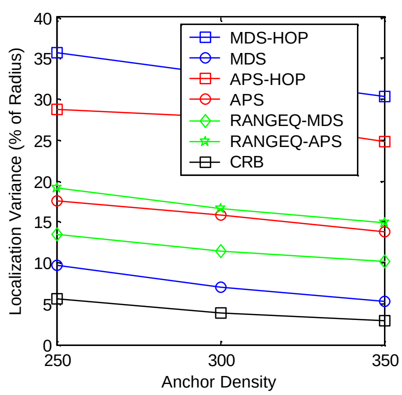


Figure 6: *Localization error variance: Anchor ratio is 10%, and σ_{np} is 0.045.*

For path-loss index (exponent),Figure 7 shows similar localization error variance increasing trend in all the algorithms except that RangeQ is less range-error sensitive than the range-aware APS and MDS. For a smaller path-loss variance, localization error variance of RangeQ is close to the range-based algorithms and $20 - 40\%$ better than the range-free ones. Figure 7 also shows that when the path-loss index error is smaller, MDS localization variance is very close to CRB.

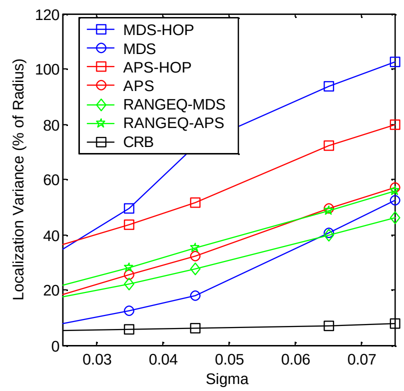


Figure 7: *Localization error variance: Anchor ratio is 10%, and communication radius is 250.*

Table 2: *Accuracy and Variance Ranking*

Algorithms	***Ranking***
MDS	1
RangeQ-MDS	2
APS	3
RangeQ-APS	4
APS-HOP	5
MDS-HOP	6

3.5 Overall Performance Ranking

Based on the result shown in Figures 2-7, a general performance ranking table is created (Table 2). MDS is the best for both precision and accuracy while RangeQ lies in between range-aware and range-free MDS and APS. From Table 2, we can clearly see the correlation between the performance of RangeQ-based algorithms and their stand-alone range-aware versions. RangeQ can improve the performance of a range-free localization algorithm, but the degree of improvement depends on the range-free algorithm itself, which shows both the advantage and disadvantage of RangeQ.

4 Conclusions

This paper combines two key localization performance metrics: localization precision and localization accuracy. We have designed an experimental framework to evaluate localization methods. Using this framework, we have evaluated MDS, APS, MDS-HOP, APS-HOP, RangeQ-MDS and Range-APS. Based on the metrics and three network parameters that affect localization performance, simulation experiments are performed on six localization algorithms, and their performances are systematically evaluated. The simulation result shows that the RangeQ range estimation method can improve both the localization accuracy and variance by $20-40\%$ of the radio range. This proves that RangeQ is a solid method when RSSI is available but a radio model is undefined or difficult to measure the parameters. Moreover, a ranking list is composed based on the simulation result which may help in making algorithm choices under different network setup.

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