Path Planning of Mobile Landmarks for Localization in Wireless Sensor Networks

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Abstract

Many applications of wireless sensor networks require the sensor nodes to obtain their locations. The main idea in most localization methods has been that some nodes with known coordinates (e.g., GPS-equipped nodes) transmit beacons with their coordinates in order to help other nodes to localize themselves. A promising method that significantly reduces the deployment cost is to replace the set of statically deployed GPS-enhanced sensors with one mobile landmark equipped with a GPS unit. In this case, a fundamental research issue is the planning of the path that the mobile landmark should travel along in order to minimize the localization error.

In this paper we first study the localization error of three different trajectories for the mobile landmark, namely SCAN, DOUBLE SCAN, *and* HILBERT. *We further study the tradeoffs between the trajectory resolution and the localization accuracy in the presence of 2-hop localization, in which sensors that have already obtained an estimate of their positions help to localize other sensors. Our trajectories are practical and can be easily implemented in mobile robot platforms.*

Keywords*: Wireless sensor networks, localization, mobile robots, mobile landmarks, path planning*

1. Introduction

Many applications of wireless sensor networks require the sensor nodes to obtain their locations. A trivial method for sensor localization is for the sensors to be equipped with GPS [24]. However there are several arguments against this architecture related to cost, power consumption, and deployability of GPS-equipped sensor nodes due to increased form factor.

To mitigate such issues with GPS deployment on sensors, several distributed localization schemes have been proposed that do not require GPS on all sensor nodes [13, 4, 20, 10, 3, 7, 19]. In this case, only a fraction of the sensors have GPS units and these sensors transmit their coordinates to the rest of the sensors to help them localize themselves. A promising method to localize sensor networks is to use one mobile landmark, e.g., a mobile robot [15, 6, 21, 5]. Such mobile landmarks are equipped with GPS units and move throughout the sensor network area providing sensor nodes with their locations. Such an architecture offers significant practical benefits. The size of a robot is much larger than the size of a sensor and thus it is much easier to install a GPS unit on it. Moreover, a robot is not as energy constrained as a sensor. Since the localization accuracy can always be improved by increasing the resolution of the movement trajectory if the mobile landmark can move arbitrarily faster, a fundamental research issue when using a mobile landmark is the planning of the movement trajectory of the mobile landmark in order to maximize the localization accuracy, for a given velocity of the mobile landmark.

In this paper, we study the design of mobile landmark trajectories to maximize the localization accuracy for sensor networks. We first show that a carefully selected deterministic trajectory can guarantee that all the sensors receive beacons and obtain an estimate for their positions, and it significantly reduces the average localization error, compared to random movement. We examine in detail three different deterministic trajectories, namely SCAN, DOUBLE SCAN, and HILBERT. Our results show that among the three trajectories, SCAN offers the best performance when the trajectory has a fine resolution, i.e., the average distance between the sensors and the trajectory is small. But for trajectories with a coarse resolution, HILBERT is the best choice. To our knowledge, this is the first study of mobile landmark trajectories for sensor network localization.

We further study the tradeoffs between the resolution of trajectories and the localization accuracy in the presence of

2-hop localization, in scenarios with sensor mobility. The location errors for a set of mobile sensors come from two sources: the error from the localization algorithm itself, and the sensor's own movement before it can perform the localization operation again, i.e., when the mobile landmark finishes a complete round traversing the network area and the beacons can reach the sensor again. There is a delicate tradeoff between the two error sources by adjusting the resolution of the mobile landmark's trajectory. For example, having the mobile landmark travel along a more refined trajectory can reduce the error from the localization algorithm, but elongates the duration between consecutive localization operations and hence the error from sensor movement. Conversely, having it travel along a coarser trajectory can cause certain sensors not to be localized as they are far away from the trajectory; such sensors have to resort to 2-hop localization, i.e., be localized using beacons emitted from other sensors that have been localized using beacons sent from the mobile landmark. However, 2-hop localization can introduce accumulative error. Our simulation study shows that with a moderate sensor mobility and using the HILBERT trajectory, 2-hop localization reduces the localization error by about 40% compared to 1-hop localization.

2. Related Work

There has been a large body of research on localization for wireless sensor networks over the last few years. They share the same main idea that nodes with unknown coordinates are helped by one or more nodes with known coordinates (e.g. GPS-equipped nodes) in order to estimate their positions. Most of these works consider static landmarks [1, 3, 4, 7, 10, 11, 12, 13, 14, 17, 19, 20, 23]. In the rest of this section we briefly describe schemes that use mobile landmarks.

Static sensors, mobile landmarks In schemes of this category, only one mobile landmark (e.g. a robot, a man, or a vehicle) is used in order to localize a set of static sensors. The landmark traverses the deployment area and either periodically transmits beacons with its coordinates to help sensors to estimate their positions ([6, 5, 21]), or receives beacons transmitted by unknown nodes and estimates their positions, applying some signal processing technique [15].

All of the above approaches, however, only consider random movement for the mobile landmark. In [21], the authors discuss the problem of optimal mobile landmark trajectory, but only discuss guidelines on selecting a good trajectory, and do not propose any specific solution.

Different from the previous schemes, [16] proposes Mobile-Assisted Localization (MAL), an algorithm that guides the robot in order to collect the necessary pairwise distances from nodes in order to perform localization. In our approach the robot is not sent explicitly to each node, but it follows an assigned trajectory which guarantees that all sensor nodes will be able to receive beacons from it.

Mobile networks - mobile sensors and landmarks The Monte Carlo localization (MCL) method [9] is the only method which can be used in mobile sensor networks (where both nodes and landmarks can move) to exploit mobility and increase accuracy of location estimation. It gives satisfactory results, but requires a very high density of mobile landmarks (1 landmark per transmission range is required for an accuracy of 40% of the radio range). In Section 5, we examine how a *2-hop localization* scheme, based on *Iterative Multilateration* proposed in [19], along with a carefully selected trajectory, can mitigate the mobility problem by using only one mobile landmark.

3. Background - Localization Algorithm

In studying the effectiveness of different mobile landmark trajectories, we use the localization algorithm proposed by Sichitiu et al. [21] which uses the Received Signal Strength Indicator (RSSI) for ranging and Bayesian inference to estimate the positions of the unknown nodes. However, the specific localization algorithm is orthogonal to our study and hence we expect our findings to remain valid when other RF-signal-based schemes are used (for example, [5], [6]).

Before running the algorithm, an offline calibration phase is needed to construct the PDF Table. This table is stored at each node and maps every RSSI value to a Probability Distribution Function (PDF). According to the algorithm, the mobile landmark periodically broadcasts beacon packets as it traverses the deployment area. These packets contain the coordinates of the mobile landmark, which can be obtained by GPS. When a node receives a beacon packet, it performs a lookup at the PDF Table and obtains the probability distribution function of the distance corresponding to the RSSI of the beacon packet. Using this function, the sensor imposes a constraint on its position estimation.

Bayesian inference is then applied and the new position estimate is computed for the node being localized, based on the old position estimate and the new constraint. This process is repeated for each received beacon packet. Finally, when the node stops receiving any more beacon packets, either because the mobile landmark has moved away, or because a maximum number of beacons has been received, the node computes its position coordinates as a weighted average of its last position estimate over the whole deployment area.

4. Mobile Landmark Trajectories

In this section, we describe three different trajectories that are evaluated in this paper: SCAN, DOUBLE SCAN, and HILBERT. For each trajectory, we describe its basic characteristics, followed by a brief qualitative discussion on their advantages and disadvantages.

SCAN SCAN is a simple and easily implemented trajectory. The mobile landmark traverses the network area along one dimension, as shown in Figure 1(a). In this figure, the mobile landmark travels along the y-axis, and the distance between two successive segments of the trajectory, parallel to the y-axis, defines the resolution of the trajectory. If the communication range of the sensors is R, the resolution should be at most $2R$, to make sure that all the sensors will be able to receive beacons.

SCAN has the advantage of offering uniform coverage to the whole network, and it ensures that all nodes will be able to receive beacons from the mobile landmark under a properly selected resolution. Moreover, uniformity keeps the maximum error low, as we will show in Section 6. However, SCAN has one important drawback – collinearity of beacons. When the resolution is larger than the transmission range, many nodes will receive beacons only from one line segment and one direction, which will prevent them from obtaining a good estimate along the x-axis.

DOUBLE SCAN Another straightforward way to overcome the collinearity problem of SCAN is to scan the network along both directions, as shown in Figure 1(b). The problem with this method is that it requires the mobile landmark to travel doubled distance, compared to the simple scan, for the same resolution. In Figure 1(b), we selected to keep the distance traveled by the mobile landmark similar for all trajectories, hence DOUBLE SCAN is performed with a doubled resolution compared to SCAN.

HILBERT A HILBERT space-filling curve [8] creates a linear ordering of points in a higher-dimensional space that preserves the physical adjacency of the points. A level-*n* HILBERT curve divides the 2-dimensional space into 4^n square cells and connects the centers of those cells using 4^n line segments, each of length equal to the length of the side of a square cell. We define the resolution of the HILBERT curve as the length of each line segment, as shown in Figure 1(c).

The key reason we study HILBERT curves in this paper is that such curves make many turns, compared to SCAN or DOUBLE SCAN. This implies that if the mobile landmark moves on a HILBERT curve, the sensors to be localized will have the chance to receive *non-collinear* beacons and obtain a good estimate for their positions.

It can easily be shown that the total distances traveled by the mobile landmark with HILBERT, SCAN and DOUBLE SCAN are given by:

$$D_{Hilbert} = 4^n \times R \quad (1)$$

$$D_{Scan} = (4^n - 1) \times R \quad (2)$$

$$D_{DoubleScan} = (4^n + 2^n - 4) \times R \quad (3)$$

where n is the level of the HILBERT curve and R is the resolution of the trajectory. Equations 1 and 2 show that the total distances for HILBERT and SCAN differ only by R.

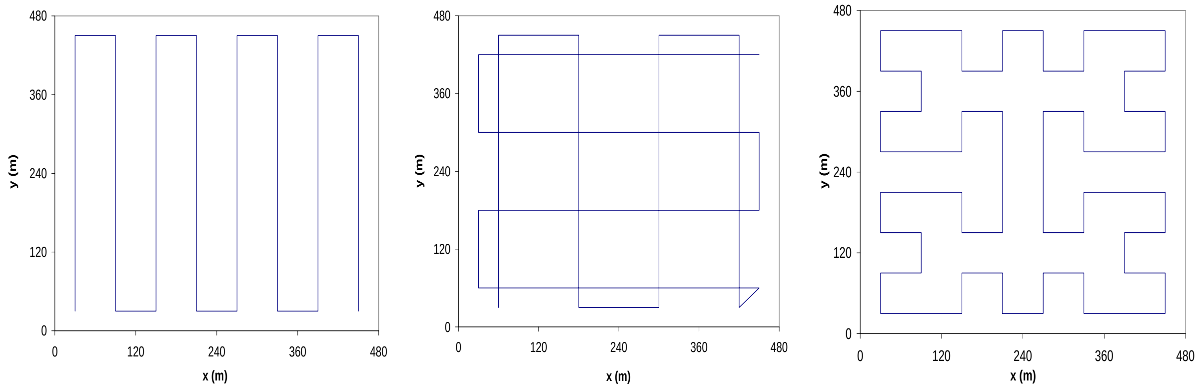
5. Multihop Localization

In a mobile scenario, the location error of sensors comes from two sources. One source is the localization algorithm itself, due to the inherent inaccurate translation of signal strength values to distances through the PDF Table. This source also exists in static scenarios. The other, which appears only in mobile scenarios, is the sensor's movement between two consecutive localization epochs. We define a *localization epoch* as the duration in which the mobile landmark traverses the whole network area once.

There is a delicate tradeoff between the two error sources by adjusting the resolution of the mobile landmark's trajectory. The localization error can be reduced by having the mobile landmark travel along a more refined trajectory, as the sensors will be able to receive more beacons and from closer distances. However, a refined trajectory elongates the duration between two consecutive localization epochs and hence increases the error from sensor movement.

The error from sensor movement can be reduced by having the mobile landmark travel along a very coarse-grained trajectory. However, certain sensors may not receive any beacons and remain unlocalized, because they are far away from the trajectory. For these sensors, *multihop localization* could be used to perform localization. The idea of a multihop localization scheme was first proposed in [19], as well as in [22], but in both works it was only evaluated for static networks (static sensors/static landmarks). In multihop localization, nodes that receive beacons directly from the mobile landmark and obtain an estimate about their locations, broadcast beacons with their own position estimates. This allows the nodes that are far away from the mobile landmark to localize themselves by using beacons emitted by other nodes. Multihop localization, however, can cause accumulative error, since nodes localized using location estimates from other nodes inherit the localization error in those location estimates.

To limit the error accumulation, we incorporated multihop localization into our localization algorithm as follows. A sensor sends out a beacon of its own which contains its position estimate only if the two following conditions are met. First, it should have received at least three beacons from the mobile landmark or other sensors. Second, a large percentage of the beacons it has received should be from the mobile landmark. Since only nodes that hear the mobile landmark can meet these two conditions, multihop localization is effectively reduced to *2-hop localization*.



(a) SCAN, deployment area $420m \times 420m$, resolution $60m$, total distance traveled 3780m.

(b) DOUBLE SCAN, deployment area $420m \times 420m$, resolution $120m$ total distance traveled 4080m.

(c) HILBERT, deployment area $420m \times 420m$, resolution $60m$, total distance traveled 3840m.

Figure 1. The mobile landmark trajectories studied in the paper.

6. Performance Evaluation

6.1. System Calibration

Before running the localization algorithm, a system calibration phase is necessary in order to construct the PDF Table, which is used by the algorithm. Following the method proposed in [21], [22], [18], we used two nodes, one sender and one receiver, in our simulator (Glomosim [25]), placing them in different distances between 2.5m and 50m. The communication range of the two nodes was set to $40m$. A wireless radio with 2 Mbps bit rate was used. To make the simulation realistic, we used a Rician fading model, with a Rician k-factor = 5. For each distance, we took 1600 measurements of the signal strength. For each signal strength value, we computed the mean distance and the standard deviation, assuming that the probability distribution function of the RSS vs. distance is Gaussian, and we stored this information in the PDF Table. We found that this assumption is valid for RSS values higher than -80dBm. For RSS values lower than -80dbm the standard deviation was very large, hence we did not include those values in the PDF Table.

6.2. Comparison of Different Trajectories

In this section, we evaluate the performance of three different mobile landmark trajectories, SCAN, DOUBLE SCAN and HILBERT. We consider three different resolutions for each trajectory: 30m, 45m and 60m. The deployment area dimensions are set equal to $450m \times 450m$, $675m \times 675m$ and $900m \times 900m$, respectively. The same node density is used in the three areas, and the numbers of sensor nodes are 660, 1485, and 2640, respectively. The sensors are randomly placed in the deployment area. In all scenarios, sensors are static and a mobile landmark (robot) moves around them. The speed of the robot is constant and equal to 2m/s and the beacon transmission interval is 2.5 seconds. The simulation results are averaged over 10 runs.

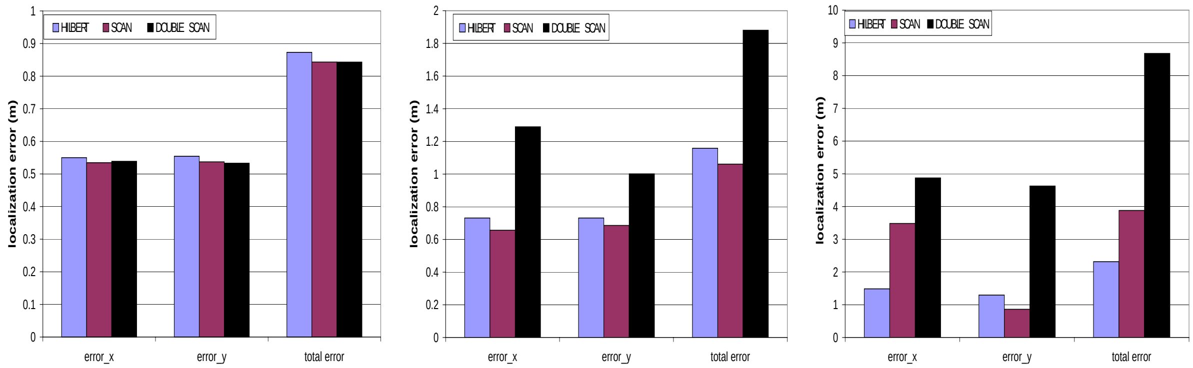
To measure the localization accuracy under different trajectories, we measure the distance between the actual and the estimated position of a sensor. We consider the average localization error over all sensors. We also show the error along the x- and the y-axis separately.

Resolution 30m Fig. 2(a) shows that the average total localization error remains very small, lower than 1m, for all three trajectories. SCAN and DOUBLE SCAN have almost the same localization error, and they both slightly outperform HILBERT by 3.5%.

Due to the fine granularity, any node is always able to receive beacons from at least two different line segments, even with SCAN trajectory, and the intersection of the constraints imposed by the two beacons eliminates ambiguity. Hence the localization error with such a small resolution is only affected by the distances from which sensors receive beacons with each trajectory. From the geometry of the trajectories it is easy to see that the maximum distance for a beacon is 15m for SCAN and 21.2m for HILBERT. This justifies why SCAN achieves lower localization error than HILBERT .

Finally, the error with DOUBLE SCAN is the same as the error with SCAN, although it scans along both directions, because DOUBLE SCAN is performed with a double resolution. In this case, the advantage we get from the 2-D scanning is counterbalanced by the fact that many nodes receive beacons with low signal strength and the distances corresponding to them have large standard deviations.

Resolution 45m Figure 2(b) shows that the increased resolution affects both the absolute values for the localization



(a) Resolution 30m (b) Resolution 45m (c) Resolution 60m

Figure 2. Localization error for three different resolutions.

errors and the relative performance of the three trajectories. In particular, the average localization error is now increased by 33%, 26% and 123% for HILBERT, SCAN, and DOUBLE SCAN respectively. The robot now does not pass as close to the nodes as in the previous case, hence many beacons have lower signal strengths and thus larger standard deviations, which increase the error.

Surprisingly, SCAN still gives the lowest localization error, outperforming HILBERT and DOUBLE SCAN by 9% and 77% respectively. In case of SCAN, most nodes are still able to receive beacons from two directions (left and right) and resolve the ambiguity in their location estimation.

Resolution 60m The results for the localization error are shown in Figure 2(c). The resolution here is much larger than the transmission range and this increases the error more than 100% for all the three trajectories. Compared to the 45m resolution, the total localization error increases by factors of 2, 3.5, and 4.5 for HILBERT, SCAN, DOUBLE SCAN, respectively.

Figure 2(c) shows a significant disparity between the errors in the x-axis and y-axis for SCAN – the error along x-axis for SCAN is 4 times larger than the error along the y-axis, while for the other two trajectories the error is similar along the two axes. This is because with SCAN and the 60m resolution, about 66% of the nodes are able to receive beacons from only one line segment (one direction). With DOUBLE SCAN, which is performed with doubled resolution, only a small percentage of the nodes can receive beacons from at least two segments, similarly to SCAN. The rest of the nodes are equally likely to be close to a segment parallel to either the x- or y-axis, and hence on average, the error is similar along both axes. In contrast, HILBERT trajectory is the only trajectory with which nodes can always receive beacons from at least two different line segments.

Due to the large percentage of nodes receiving only collinear beacons in case of SCAN and DOUBLE SCAN, the main factor that affects the localization error is shifted from the distances between the sensors and the mobile landmark to the collinearity of received beacons. As a result, HILBERT has now the smallest localization error among the three trajectories, outperforming SCAN and DOUBLE SCAN by 69% and 278%, respectively.

6.3. Multihop Localization

In this section, we evaluate the impact of the trajectory resolution on the localization accuracy in the presence of multihop localization in scenarios with mobile sensors. We use 2 different resolutions for the robot trajectory: $60m$ and $120m$. With the first resolution, all nodes can receive beacons from the robot, and thus 2-hop localization is not needed. The second resolution however is very large (3 times the transmission range), and 2-hop localization is used so that all the sensors can obtain some estimate about their position. In 2-hop localization, sensors which have received at least 80% of their total beacons from the robot also transmit beacons. In the following, *1-hop localization* refers to using $60m$ trajectory resolution and 1-hop localization, and *2-hop localization* refers to using $120m$ trajectory resolution and 2-hop localization.

Since we are interested in traversing the network with a coarse resolution, we use the HILBERT space filling curve as the robot trajectory, which has been shown in Section 6.2 to give the smallest localization error when the resolution coarsens.

In this experiment, we only consider the largest of the three areas used in Section 6.2, with dimensions $900m \times 900m$. The 2640 sensors are again placed randomly in the area, but this time they move. We use a modified version of the random waypoint model [2] to describe the movement of the sensors. The pause time is set to 0, and all the sensors move with the same velocity. We consider three different velocities for sensors: $1m/h$, which simulates a very low mobility scenario, $30m/h$, and $60m/h$. The speed of the robot is kept to $2m/s$.

Sensor velocity $1m/h$ In this case, the sensors have very low mobility. In one epoch a sensor may travel a maximum distance of $2.1m$ on the same direction, which implies that the localization error for a sensor in one epoch cannot increase more than $2.1m$, because of its movement. Hence, the main source of error with this velocity is the localization error incurred when the sensors execute the localization algorithm. Figure 3(a) shows that *1-hop localization* significantly outperforms *2-hop localization*. The average localization error for *1-hop localization* has increased from $2.3m$ in the static scenario of Figure 2(c) to $3.5m$, but it remains lower than 5m and, more importantly, almost constant over time. On the other hand, *2-hop localization* does not offer any benefit in this case, but it increases the error, which oscillates between $31m$ and $38m$.

Sensor velocity $30m/h$ In this case, the velocity of the sensors is quite large, and the two sources of error contribute almost equally to the total error. Since mobile landmark repeats the same trajectory periodically, the average localization error over time also has some periodicity, as shown in Figure 3(b). In this figure, we observe that the average localization error oscillates between 27m and 36m over time for *1-hop localization* and between 33m and 37m for *2-hop localization*. Although the average error over time is still smaller for *1-hop localization*, the difference now is very small and there are also periods of time where *2-hop localization* outperforms *1-hop localization*. With *2-hop localization*, sensors never get the chance to obtain a very accurate estimate, since the mobile landmark does not pass close to most of them, but their estimates never become too stale. This is reflected in the variation of the average localization error over time for the two curves of Figure 3(b), which is about 10m for *1-hop localization*, while it is only 4m for *2-hop localization*.

Sensor velocity $60m/h$ In this case, the sensors mobility is the main source of error, rather than the error caused by the localization algorithm. Figure 3(c) shows that the average error for *2-hop localization* oscillates between 40m and 52m, while it oscillates between 52m and 76m for *1-hop localization*. Hence, *2-hop localization* clearly outperforms *1-hop localization*. On average *2-hop localization* reduces the localization error by about 40%. Also, the variation of the error with *2-hop localization* is only about 12m, half of the variation observed with *1-hop localization*.

Note that although an error of 40m or 50m seems very large compared to the error of 2m or 3m as seen in Section 6.2, this is the best we can achieve when sensors move at such a high velocity and using a single mobile landmark. This accuracy is still useful in some applications, e.g., geographic routing and animal monitoring. Moreover, this accuracy is achieved by using a single mobile robot, which has a very low cost. The only work other than ours that considers sensor mobility [9] achieves an error of about 25m by using 1 mobile landmark per transmission range, for a total of 160 mobile landmarks in an area of $900m \times 900m$ and a transmission range of $40m$.

7. Conclusions

In this paper we have studied the problem of path planning for mobile landmarks to reduce the localization error. Specifically, we studied three different deterministic trajectories for use by a mobile landmark in sensor network localization. Our performance results show that among the three trajectories, SCAN offers the best performance when the trajectory has a fine resolution, i.e., the average distance between the sensors and the trajectory is small. However, for resolutions that are larger than the transmission range, the HILBERT space-filling curve outperforms SCAN by about 69%. We also studied the path planning problem in scenarios where sensors have moderate mobility. In such scenarios, we showed that the average localization error can be significantly reduced over time, by using a large trajectory resolution combined with *2-hop localization*, in which nodes that obtain a good estimate about their positions help other nodes to localize themselves.

Our trajectories are practical and can be easily implemented in mobile robot platforms (for example, [26]). Additionally, most mobile robot control software can detect obstacles that arise in the planned path (e.g., using sonar), and dynamically adjust the robot's movement to travel around them. Subsequently, the robot can re-align with the planned path.

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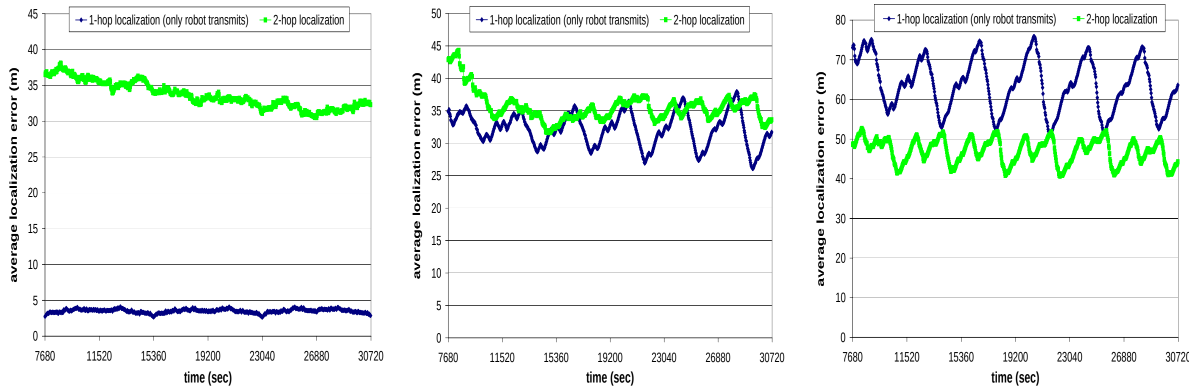

(a) Sensor velocity 1m/h

(b) Sensor velocity 30m/h

(c) Sensor velocity 60m/h

Figure 3. Average localization over time for three different sensor velocities.

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