The Key Metric forEvaluation Localizationin Wireless Sensor Networks via Distance/Angle Estimation Algorithm (D/A-EA)

Reza Godaz[1], Mohammad Reza KaghazGaran[2]

[1]Islamic Azad University, Mashhad Branch,Department of SoftwareComputer Engineering, Mashhad, Iran.

rgodaz@mshdiau.ac.ir

[2]Islamic Azad University, Mashhad Branch,Department of SoftwareComputer Engineering, Mashhad, Iran.

kaghazgaran@mshdiau.ac.ir

Abstract

Wireless sensor network localization is an importantarea that attracted significant research interest.. Hence, localization schemes for wireless sensorAlthough mobility would appear to make localization more difficult, in this paper We present a new method bywhich a sensor node can determine its location by listening to wireless transmissions from three or more fixed beacon nodes and argue that it can exploit mobility to improve the accuracy and precision of localization. Our approach does not require additional hardware on the nodes and works even when the movement of seeds and nodes is uncontrollable. The proposed method is based on aDistance/ Angle- Estimation technique that does not increase the complexity or cost of construction of the localization sensor nodes. It determines how the available information will be manipulated to enable all of the nodes of the WSN to estimate their positions. It is a distributed and usually multi-hop algorithm.

Keywords:

Wireless sensor network- mobility-multi-hop algorithm

1. INTRODUCTION

Location awareness is important for wireless sensor networks since many applications such as environment monitoring, vehicle tracking and mapping depend on knowing the locations of sensor nodes. In addition, location-based routing protocols can save significant energy by eliminating the need for route discovery [17, 16, 15] and improve caching behavior for applications where requests may be location dependent [14]. Security can also been enhanced by location awareness (for example, preventing wormhole attacks [13, 12]). However, putting GPS receivers in every node or manually configuring locations is not cost effective for most sensor network applications.

Recently some localization techniques have been proposed to allow nodes to estimate their locations using information transmitted by a set of seed nodes that know their own locations .We

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are interested in performing localization in a more general network environment where no special hardware for ranging is available, the prior deployment of seed nodes is unknown, the seed density is low, the node distribution is irregular, and where nodes and seeds can move uncontrollably. Although mobility makes other localization techniques increasingly less accurate, our the node distribution is irregular, and where nodes and seeds can move uncontrollably. Although mobility makes other localization techniques increasingly less accurate, our technique takes advantage of mobility to improve accuracy and reduce the number of seeds required networks typically use a small number of seed nodes that know their location and protocols whereby other nodes estimate their location from the messages they receive.

2. Related Work

In sensor networks, nodes are deployed into an unplanned infrastructure where there is no a prioriknowledge of location. The problem of estimating spatial-coordinates of the node is referred to aslocalization. An immediate solution which comes to mind is GPS [2] or the Global Positioning System.

However, there are some strong factors against the usage of GPS. For one, GPS can work only outdoors.Secondly, GPS receivers are expensive and not suitable in the construction of small cheap sensor nodes. A third factor is that it cannot work in the presence of any obstruction like dense foliage etc. Thus, sensor nodes would need to have other means of establishing their positions and organizing themselves into a coordinate system without relying on an existing infrastructure.

Localization can be classified as fine-grained, which refers to the methods based on timing/signal strength and coarse-grained, which refers to the techniques based on proximity to a reference point. One way of considering sensor networks is taking the network to be organized as a hierarchy with the nodes in the upper level being more complex and already knowing their location through some technique .These nodes then act as beacons by transmitting their position periodically. The nodes which have not yet inferred their position listen to broadcasts from these beacons and use the information from beacons with low message loss to calculate its own position. A simple technique would be to calculate its position as the centroid of all the locations it has obtained. This is called as proximity based localization. It is quite possible that all nodes do not have access to the beacons. In this case, the nodes which have obtained their position through proximity based localization themselves act as beacons to the other nodes.

3. Localization Protocol

The constraints in sensor nodes and ranging precision make localization for mobile sensor nodes a more difficult problem than robot localization. On the other hand, scale can be used to our advantage. The many nodes in a sensor network can cooperate to share location information. We assume time is divided into discrete time units. Since a node may move away from its previous location, it needs to re-localize in each time unit. We are interested in obtaining the probabilistic distribution of a node's possible locations. Localization systems can be divided into three distinct components see Fig. 1 .As a node moves in the network, prior location information will become increasingly inaccurate. On the other hand, there are new observations from seed nodes that are able to filter impossible locations. The posterior distribution of a node's possible locations after movement and observation is not easy to determine. Except for a few special cases including linear Gaussian state space models [11], it is impossible to evaluate the distribution analytically [12].

The Sequential Monte Carlo (SMC) method [10] provides simulation-based solutions to estimate the posterior distribution of nonlinear discrete time dynamic models. The key idea of SMC is to represent the posterior distribution by a set of m weighted samples, and to update them recursively in time using the importance sampling method [9]. Since the unconditional variance of the importance weights will increase [18], re-sampling techniques [19] are used to eliminate trajectories with small normalized importance weights. SMC has been successfully applied in targetracking [20], robot localization [5] and computer vision [4]. We provide a brief introduction below. A more detailed introduction can be found in [21], and an overview and discussion of SMC's properties can be found in [3].

Sensor nodes must determine their locations with respect to some fixed beacon nodes using wireless or infrared signals and possibly engaging in cooperative computations. Existing location discovery techniques typically use distance or angle measurements from a fixed set of reference points and apply multi-literation or triangulation techniques to solve for the unknown location. The distance or angle estimates may be obtained from:

- Received signal strength (RSSI) measurements: where knowledge of the transmitter power, the path loss model, and the power of the received signal are used to determine the distance of the receiver from the transmitter. A sensor node estimates the distances from three of more beacon nodes to compute its location. The major drawback of this method is that multi-path reflections, non-line-of-sight conditions, and other shadowing effects might lead to erroneous distance estimate.

- Time-of-arrival and time- difference- of- arrival (TOA, TDOA) measurements: which may be used to estimate the distance from a set of reference points by measuring the propagation times (or differences thereof) of the signals. Hence, when a dense network is involved, such as a sensor network, localization techniques using TOA or TDOA measurements need to use a signal that has a smaller propagation speed than wireless, such as ultra-sound [16].

- Angle of arrival (AOA) measurements: where special antenna configurations are used to estimate the angle of arrival of the received signal from a beacon node. A prototype navigation system described in [12] is also based on a similar concept but it uses a set of optical sources and a rotating optical sensor for obtaining the angular measurements.

3.1 Location Estimation Algorithm

The mobile localization problem can be stated in a state space form as follows. Let t be the discrete time, $l_t$denote the position distribution of the node at time t, and o_t denote the observations from seed nodes received between time t-1 and time t. A transition equation p ($l_t | l_{t-1}$) describes the prediction of node's current position based on previous position, and an observation equation p (l_t| o_t) describes the likelihood of the node being at the location $l_t$given the observations. We are interested in estimating recursively in time the filtering distribution p (l_t | o_0, $o_1 \ldots o_t$). A set of N samples L_t is used to represent the distribution l_t and our algorithm recursively computes the set of samples at each time step. Since L_{t-1} reflects all previous observations, we can compute l_t using only L $_{t-1}$ando_t. Initially, we assume the node has no knowledge about its position, so the initial samples are selected randomly from all possible locations. At each time step, the location set is updated based on possible movements and new observations. We estimate the location of the node by computing the average location of all possible locations in Lt. For our experiments, we assume locations are (x, y) positions in two dimensional Cartesian spaces, but the technique could be used equivalently for three dimensions or other location representations.

3.2 Filtering

In this step, the node filters the impossible locations based on new observations. For simplification of presentation and analysis, we assume that time is discrete and all messages are received instantly. Hence, at time t, every node within radio range of a seed will hear a location announcement from that seed. In a realistic deployment, it would be necessary to deal with network collisions and account for missed messages. Fig. 3 shows an example situation. There are four types of seeds to consider:

Outsider's seeds that were not heard in either the current or the previous time quanta. Arriver seeds that were heard in the current time quantum, but not in the previous one. Leavers– seeds were heard in the previous time quantum, but not in this one. Insiders – seeds that were heard in both time quanta. Arrivers and leavers provide the most useful information since the node will know it was within distance r of $l_0$at timet_0, but not within distance r of l1 at timet_1. If we only rely on direct information from seeds, however, a node will not know the previous location of an arriver, or the current location of a leaver. There are two possible ways to gather this information:

1. A seed node (S) transmits both its current location andits location at the previous time step in each announcement:

   $S \rightarrow$ Region HELLO | ID_S | l_{oct}| l_{oct-1}

20. Neighbor nodes can transmit information about seed locations:

   $S \rightarrow$ Region HELLO | ID_S | l_{oct}

   $N \rightarrow$ Region HELLO | ID_N | {(IDS, l_{oct}

) }

The second approach is more expensive, but its cost may be combined with neighbor discovery in applications that require neighborhood information for other purposes. The advantage of the second approach is it also allows nodes to discover information about outsider seeds without keeping track of arrivers and leavers. The node knows it is not within distance r of any outsider seed, but must be within distance 2r of any seed heard by one of its neighbors, time 0 To position l_1 on time 1. The seed is an insider for nodes in region III, an arriver for nodes in region II, a leaver for nodes in region I, and an outsider for all other nodes.

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4. Evaluation

The key metric for evaluating a localization technique is the accuracy of the location estimates versus the communication and deployment costs. Increasing the density of seeds or the frequency of location announcements should improve accuracy, but the tradeoffs need to be understood to determine appropriate deployment parameters. In this section, we evaluate the D/A-EA technique by measuring how its estimated location errors vary with various network and algorithm parameters described in Section 4.1. In addition, we compare our results to those for other range-free localization techniques, namely the [1].

4.1 Simulation Parameters

In our experiments, we vary parameters of both the sensor network and sensor nodes, and of the D/A-E Algorithm. For all of our experiments, sensor nodes are randomly distributed in a 500m x 500m rectangular region. We assume a fixed transmission range, r of 50m for both nodes and seeds. The network and node parameters we vary are:

- Speed of the nodes and seeds (v_{max},v_{min}, s_{max},s_{min},). We represent the speed as the moving distance per time unit. A node's speed is randomly chosen from [v_{min},v_{max}]; a seed's speed is randomly chosen from [s_{min}, v_{max}]. We consider the impact of speeds on both accuracy and convergence time.

- Node density (n_d), the average number of nodes in one hop transmission ranges. We study the effects of varying n_d use a fixed n_d = 10 for other experiments.

- Seed density (s_d), the average number of seeds in one hop transmission range.

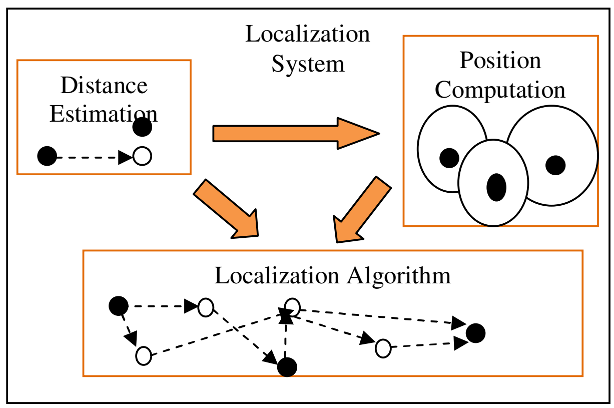

Fig. 1: The division of localization systems into three distinct components.

We adopt the random waypoint mobility model [8] for both nodes and seeds. It is one of the most commonly used mobility models for mobile ad hoc networks. . In the random waypoint model, a node randomly chooses its destination, its speed of movement, and its pause time after arriving at the destination. We assume nodes are unaware of their velocity and direction, but have a known maximum velocityv_{max}. As pointed out in [22], the random waypoint model suffers from the decay of average speed, and this will provide an unsound basis for simulation. We used a modified random waypoint model to maintain the average speed. Instead of choosing a certain speed for each destination, nodes randomly vary their speed during each movement. The pause time is set to 0, so the average speed is exactly $\frac{v_{max}}{2}$when speed is chosen randomly between 0 andv_{max}. we consider how different mobility models affect the localization accuracy.

Initialization: Initially the node has no knowledge of its location. N is a constant that denotes the number of samples to maintain:

L_0 = {set of N random locations in the deployment area}

Step: Compute a new possible location set Lt based on l_{t-1} , the possible location set from the previous time step, and the new observat

$\frac{1}{\pi v^2_{max}}$

L_t = { }

While (size (L_t) < N) do

R = { l_t^i | $l_t^i$is selected from p(l_t | l_{t-1}^i), $l_{t-1}^i$for all i ϵ N}

R $_{filtering}$ = {l_t^i | l_t^iwherel_t^iϵ R and p(o $_t$| l_t^i)>0),

L_t=choose (L_tU R $_{filtering}$ N)

p (l_t | l_{t-1})= $\frac{1}{\pi v^2_{max}}$I if distance (l_t , l_{t-1})<v_{max}

Fig. 2. Location Estimation Algorithm

We assume a node can judge if it is within radio range r of another node or not, but it cannot get more precise distance information (for example, measuring distance through received radio signal strength). For most of the experiments we model radio range as a perfect circle. This model is not realistic; however, we consider the impact of irregularity on location estimates.

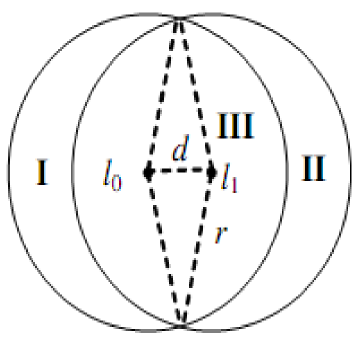

Fig. 3. Seed Movement. The seed moves from l_0 at time 0 to position l_1 on time 1

4.2 Accuracy

The accuracy of D/A-Depends on the speeds of the seeds and nodes. As time passes, nodes will receive more seed location announcements and improve their location estimates. Figure 3 shows the error in the location estimate, measured as a multiple of the node transmission distance r, for three different scenarios: stationary seeds (s_{max} = 0) with nodes moving with v_{max} = .2r and r, and both nodes and seeds moving with v_{max} = s_{max} = r.

The localization process can be divided into the initialization phase and the stable phase. In the initialization phase, the estimate error decreases dramatically as new observations are incorporated. The localization is improved by both the current observation and previous observations. In the stable phase, the impact of observations (filter) and the node's mobility (uncertainty) reach some balance, and the estimate error fluctuates around a minimum value. The faster the speed of the seeds and nodes, the quicker the stable phase is reached. The postconvergence accuracy is also better for faster moving nodes, since by moving quickly they encounter more seeds and more rapidly filter our inaccurate samples.

Unlike the D/A-EA technique, the Centroid and Amorphous localization techniques do not exploit past information, so they do not improve over time. Figure 4 compares the localization error of different localization techniques over time. The accuracy of D/A-EA improves quickly.

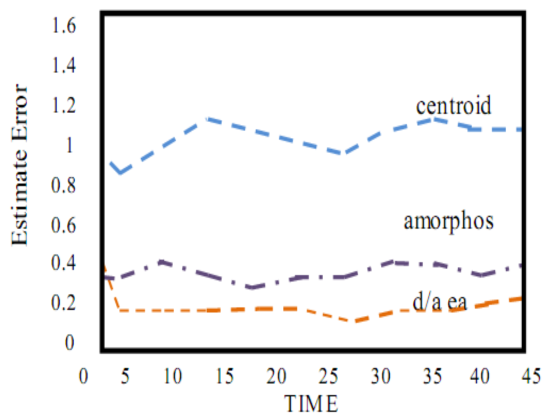

Fig. 4: Accuracy Comparison. $n_d = 10$, $s_d = 1$, $v_{max} = s_{max} = r$.

4.3 Node Speed

Varying node speed is similar to varying the time between location announcements. If announcements are more frequent, localization is more accurate but communication overhead increases. We measure maximum node speed as v_{max} and distribute actual node speeds between 0 and v_{max} using the modified random waypoint mobility model. Figure 5 shows the impact of node speed on the converged localization error as the distance traveled per announcement time unit increases from 0.1r to 2r for a few different seed densities and seed velocities. Node speed impacts the localization process in two ways. The increased speed makes the predicted locations less accurate since the next possible locations fall into a larger region. On the other hand, faster movement leads to more new observations in each time step, and hence more impossible locations can be filtered.

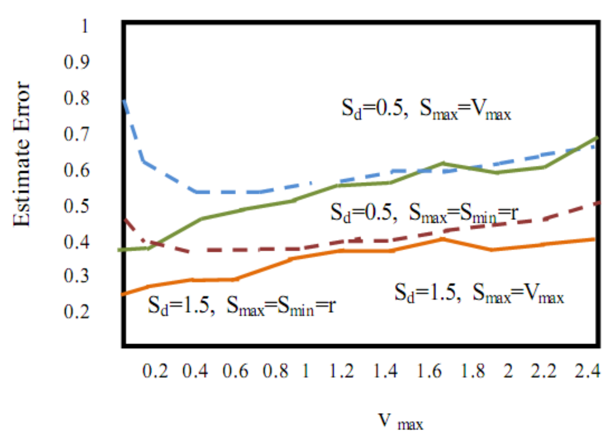

Fig. 5. Impact of node speed.

4.4 Seed Density

The estimate errors drop fast as node speeds increase from 0.1r to 0.3r when the seeds are also moving at the same speed, and then the error gradually increases as the uncertainty resulting from faster movement increases.

With fixed velocity seeds (s_{min} = v_{max} = r), the error is least when nodes are slowest, and increases gradually as nodespeed increases. Figure 5 illustrates that the length ofincreasing the density of seeds makes localization easier, but increases network and deployment costs. Figure 8 shows the average estimate error of different localization algorithms when seed density varies. The accuracy of both D/A -EA and Centroid improves as seed density increases since nodes will receive more location announcements. For the Amorphous technique, since each node receives the propagated messages from all seeds in the network, the estimate error does not improve much after there are a sufficient number of seeds (32 in this experiment). D/A -EA performs adequately even for low seed densities and outperforms the other techniques when seed density is 1 or above. Since the possible location set accounts for previous information about the node's location, D/A -EA is much more accurate than Centroid when seed density is low.

4.5 Node Density

Figure 5 shows the impact of node density on estimate error in different localization algorithms. D/A -EA and Centroid are little affected by node density. D/A -EA requires a threshold node density in order for nodes to receive two-hop when network density is below 6, but performs best when information from enough neighbors, but a few neighbors is sufficient. The Amorphous technique depends on higher network density. It performs poorly network density is larger than 15.
This is because network density has great impact on the accuracy of hop count. [23] And [24] suggest approaches for improving hop counting based techniques when the node density is low by increasing the number of seed nodes.

4.6 Motion Model

So far, we have assumed that both nodes and seeds move randomly and independently. In some applications, the motion of nodes and seeds may be correlated and demonstrate some group behavior, and this may affect the performance of our algorithm. We use the Reference Point Group Mobility model (RPGM) [15] to investigate the effect of group behavior on our algorithm. In RPGM, the motion of a node is the combination of a group motion vector and a random motion vector. The random motion is based on a reference point that moves according to the group motion. This provides an approximation for a group of nodes and seeds moving in a current or being blown by the wind.

We put all nodes and seeds in the same group. The group motion is defined as a random walk model , in which the direction is chosen randomly between 0 and 360 degrees and the speed is chosen randomly between 0 and the maximum group motion speed. Each node's individual random movement relative to the

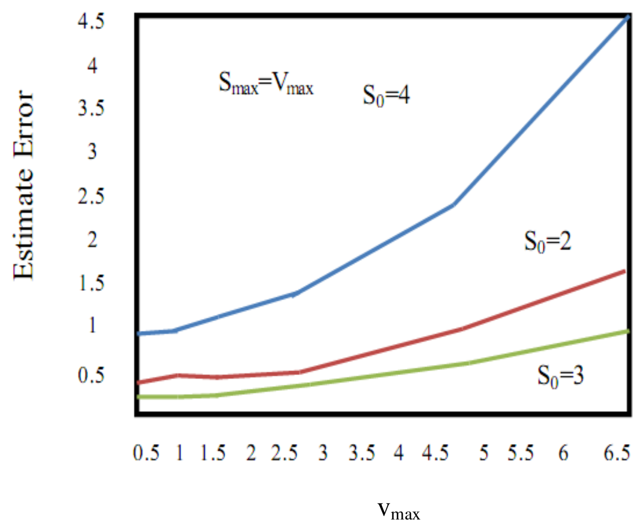

Fig. 6. Maximum Group motion speed

group motion is selected using the modified random waypoint model as in previous experiments. To maintain the same group motion for all nodes, we assume there are no boundaries in the network sonodes can move freely. If a node cannot find enough valid samples after filtering, it will reinitialize itself by eliminating previous samples and drawing samples from new observations directly. We also assume a node is awaren of the maximum distance it can move in one time unit, which is the sum of the maximum individual random movement and the maximum group motion.

The location accuracy when we keep the maximum random motion speed at r per time unit and vary the maximum group motion speed. The estimate error increases as the maximum group motion speed increases. Since all nodes are moving in the same way, the relative positions change less, so the number of useful new observations received does not increase with increasing group speed. Because the uncertainty in the prediction phase becomes larger as group motion speed increases, accuracy is substantially reduced when the group motion dominates the individual node movement. On the other hand, in some applications it may be possible to control how seeds move. A strategy that moves seeds in a way to cover the area thoroughly will improve the accuracy, and especially the convergence time, of D/A -EA.

5. CONCLUSION

Many wireless sensor network applications depend on nodes being able to accurately determine their locations. This is the first work to study range-free localization in the presence of mobility. Our main result is surprising and counterintuitive: mobility can improve the accuracy and reduce the costs of localization. Our simulation experiments .reveal that the D/A -EA technique can provide accurate localization even when memory limits are severe, the seed density is low, and network transmissions are highly irregular. Many issues remain to be explored in future work including how well our assumptions hold in different mobile sensor network applications, how different types of motion affect localization, and how our technique can be extended to provide security.

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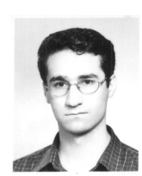
Authors

Reza Godaz

He was born in Mashhad, Iran, and received the B.Sc. and M.Sc. degree in software computer form Islamic Azad University of Najafabad, Iran, in 2002 and 2006. Since 2006 he has been a lecturer with the Islamic Azad University, Mashhad branch, Mashhad, Iran, which he joined in 2006. His research interests include Networks, Databases and Semantic Web.



Mohammad Reza Kaghazgaran

He was born in Mashhad-Iran and B.Sc. Software ComputerEngineering of Islamic Azad University of Mashhad. His researches are Wireless Sensor Network and Cryptography and Security and recently Vehicular Network &Bioinformatics.