A Study of Mobility in Ad Hoc Networks and its Effects on a Hop Count Based Distance Estimation

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***Abstract*—Hop Count based distance estimation is an important element for the distributed computation of coordinates in GPS free environments. Deriving a distance estimate from hop counts is prone to error especially when the algorithm is applied to a network of mobile devices. We define and analyze two error models to describe the origin of underestimated and overestimated distances in a mobile ad hoc network. Different movement patterns are examined to get an understanding of their impact on the length of one hop and, thus, the estimated distance. Our experiments and analysis indicate that mobility can have a positive effect on the accuracy of a distance estimate by an emerging effect of asynchronous computation and fluctuating distribution of nodes. In addition, we identify parameters, such as direction and variance in movements,that are responsible for the different influences of the presented mobility models.**

***Index Terms*—MANET; mobility; hop count; localization; error analysis;**

I. Introduction

In many applications such as geographic monitoring, smart buildings, target tracking or disaster management, a large number of possibly mobile devices is utilized to accomplish a specific goal. In general, such devices consist of low power processors, have little memory and limited wireless communication range to exchange short messages with other devices. A network of such devices is called mobile ad hoc network (MANET) as the network's connectivity is dynamic and formed ad hoc. In such networks, there is often a tradeoff between reliability and cost. Additionally, to avoid further expenses, the devices usually are not equipped with any localization technique. This makes it hard to realize applications that depend on the location of each device such as the allocation of event reporting in a monitoring sensor network [1]–[3], location dependent routing [4]–[8], support of group querying [9], pattern formation [10], [11], and many more. Therefore, alternative localization techniques were proposed for ad hoc networks (cf. [12], [13] for an overview). Many of these algorithms rely on the estimation of the distance between each node and a small number of so called anchor nodes. Anchor nodes are assumed to know their own coordinates either through a GPS-receiver or a priori configuration. There are two main ways to estimate distances. One can assess the distance between two devices by analyzing the communication signal, mostly by evaluating its strength on receipt. Another way is based on counting communication hops to the anchor node and multiplying this by an estimate for the width of such a hop. The latter is often described as Gradient Algorithm [14], [15]. In this paper, we consider a mobile ad hoc network of many devices (nodes) and analyze the effects of different mobility models on the application of the Gradient Algorithm (GA). Our goal is to quantify the error of such a gradient derived distance estimation and investigate the impact of different mobility models on the applicability of a GA. Two different error types are identified in the GA for distance estimation caused by either the distribution of the devices or mobility. Our observations and analysis indicate that many of the mobility models positively influence the error rate. Nevertheless, a high mobility can also increase the error turning the natural overestimation of the distance into an underestimation.

This paper is structured as follows. In Section II, the basics and the problem are described as well as the related work. In Section III, the different mobility models are presented that will be examined in the experiments. In Section IV, two error models are introduced that are used for interpretation of the experiments. Section V introduces the simulation environment as well as the experiment setting and shows the experiment results and interpretations. Section VI concludes the paper.

II. Basics

Our model of an ad hoc network assumes randomly distributed mobile devices on a two dimensional obstacle free plane. The mobile devices do not have global knowledge of the topology or their locations. Each device moves and can only communicate with the devices in its neighborhood. We define the neighborhood of a device as a physical neighborhood on the plane within a fixed distance r from the device. r is supposed to be much smaller than the dimensions of the plane. We assume that all the devices have the same properties (homogeneous devices), except for a seed device located at the top-left corner of the environment. The seed device is not mobile, but has the same communication radius of r.

A. Gradient Algorithm (GA)

In the Gradient Algorithm proposed by Nagpal et al. [14], the seed device initiates a gradient by sending a message including an integer value of zero to its neighbors. Each neighbor takes the minimum value it has received, increments it by one, and propagates it to its neighbors. This continues until all the devices in the environment have such a value called **hop count**.

B. Related Work

In order to estimate the distance between two nodes of a MANET with the GA, the minimum number of communication hops between the two nodes is counted and multiplied with the communication radius. [14], [16], and [17] introduce different techniques to improve the distance deduction from a gradient. In [14], an average of all communication hops in the node's neighborhood is calculated before multiplying with the radius. This improves the distance estimation as the position within a communication hop is corrected using the additional information about the hop count of all neighbors. Nevertheless, the error induced by sparse and unevenly distributed networks can still effect the distance estimation. In [17], the distance is calculated as a product of hop count and radius and then a manually chosen reduction rate, depending on the density of nodes, is employed. This takes into account that in a sparse network, one communication hop usually has a length which is less than the radius. Both approaches locally correct the distance estimation, but do not consider the effect an overestimation of the hop length has on the following nodes. In [16] this issue of varying hop length is investigated and an algorithm is proposed that adapts the length of one hop to local conditions, improving the distance estimation further. The algorithm delivers good results in both static and mobile scenarios but the impact of different mobility models is not the focus of this work. In [18], the effect of mobility on the distance estimation in a mobile ad hoc network is investigated under the critical assumption that a node knows when it is moved and refreshes its own distance estimation before having an effect on the surrounding nodes. This leads to a general improvement of distance estimation, however, the assumption corresponds to a scenario where new nodes enter a static network and therefore the improvement is due to the increased network density and not due to mobility.

III. Mobility

In this section, we briefly explain different mobility models and categorize them (similar to [19]) into *individual* and *group mobility schemes*. All mobility is performed on the devices with a certain probability in each cycle.

A. Individual Mobility Models

In individual mobility models, a node defines its next position independently from any other node in the system. In the **Random Walk (RW)** mobility model [19], every node selects a random direction and a random speed within allowed ranges and keeps on moving until a predefined distance is traveled or a predefined time has passed. This mobility model is one of the most studied models in the literature e.g., [20]. In **Chaos Move (CM)**, we slightly modify this model and let the nodes select a new random direction and speed "at each time step". This mobility scheme is supposed to keep the mobile devices in a small area around their starting position compared to the RW model. In **Random Waypoint (RWP)** model, each node selects a random target position and a speed according to the allowed ranges. Once the node reaches the target, it pauses for some cycles before it selects the next target position [19]. In this way, there is a high likelihood that the nodes spend most of their time somewhere in the middle of the environment. We design the **Random Direction Walk (RD)** model so that a node starts moving like RW until it reaches the border of the simulation area where it pauses for some cycles before it changes its direction. This move is a modification of the RWP model as the node selects its waypoints at the border of the environment. **Bounded Random Walk (BR)** is similar to CM with the difference that a node changes its speed and direction within a small range around its former values. Another variant is the so called **Gauss Markov Move (GM)** [19] in which a node selects the next direction and speed according to the following equations:

$$s_t = \alpha \cdot s_{t-1} + (1-\alpha) \cdot \mu_s + \sqrt{(1-\alpha^2)} \cdot s_g \quad (1)$$

$$d_t = \alpha \cdot d_{t-1} + (1-\alpha) \cdot \mu_d + \sqrt{(1-\alpha^2)} \cdot d_g \quad (2)$$

where s_t and d_t are the new values for speed and direction. α is a random parameter ($0 \leq \alpha \leq 1$) and s_g and d_g are chosen from a random Gaussian distribution with zero mean and standard deviation of one, μ_s and μ_d are constant values such as 0.03 and 0. In **Probabilistic Random Walk (PR)**, three possible states are defined separately for the movement in y- and x-axis directions. For the y-axis the node is moving *backward*, *forward* or it *stands still*. For the x-axis the node is moving *left*, *right*, or *stands still*. There are fixed probabilities to transit from one state to the other that emphasize continuous moves in the same direction [19].

B. Group Mobility Schemes

The group mobility models are characterized by mutual influences between the nodes which seems more natural when considering a moving swarm. In the **Column Mobility (ColM)** model [19], all nodes move randomly within the environment except for a configurable set of nodes consisting of a group leader and its followers. All followers move more or less in a row behind the leader simulating children walking in a line following their parent. All nodes that do not correspond to a leader or follower move according to CM. In the **Nomadic Move (NomM)** mobility [19] all nodes move according to the CM. Some leaders are defined and whenever a node comes within the signal range of a leader, it starts following the leader while moving randomly within the communication range of the leader. When a leader has more than 20 followers a randomly chosen node leaves the group. In **Reference Point Mobility (RefM)** model [19], each node has a virtual reference point and can move randomly within the communication range of its reference point. At each step, all reference points are moved randomly but with the same direction and speed like they are connected to each other. The movement of the reference net corresponds to the CM. We introduce the **Stream Mobility (StrM)** model to simulate devices in moving water or wind. Each node selects a random angle and speed within an allowed range. When a node moves, it submits its angle to all its neighbors and the neighbors save the latest angle they receive and modify it by adding or reducing a randomly chosen degree between 0 and 30. Thus, each node's moving angle is influenced by the angle of its latest moved neighbor.

IV. Error in Gradient Algorithm

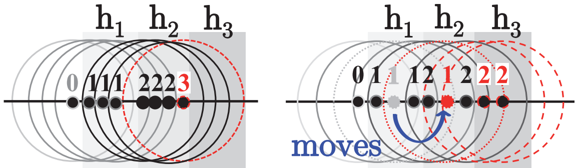
As stated before, many positioning concepts rely on distance estimation derived from hop counts. The distance estimation procedure itself can vary. To investigate the influence of mobility we take the most simple estimation method as a basis where each hop is supposed to have the width of r. This illustrates the effect of mobility on the GA more clearly than by using a modification of the algorithm. To evaluate the influence of mobility, we consider the deviation of hop counts derived by the GA from ideal hop counts when each communication hop would have an exact width of r.

Considering a perfectly dense and evenly distributed ad hoc network each device (n) would have a hop count corresponding to $h^{ideal}(n) := \lceil \frac{d(n,seed)}{r} \rceil$, where $d(n, seed)$ indicates the Euclidean distance between the node n and the seed. The communication hop h_i is the physical area, where all devices have the same ideal hop count value $h^{ideal}(n) = h_i$. Usually, the devices are not perfectly distributed and therefore we can compute the deviation from the ideal case for each node n as: $E(n) = h^{ideal}(n) - h(n)$. We call this deviation "hop count error", aware of the fact that it is not really an error but rather a deviation from an ideal case. Since it makes a difference if the hop count assigned by the GA is higher or lower than the ideal hop count, a quadratic error is not considered. The average error in a communication hop h_i is computed as:

$$E_i = \frac{1}{|H_i|} \sum_{j=1}^{|H_i|} E(j), \forall j \in H_i$$

where H_i refers to the set of nodes that are situated within the communication hop h_i. The overall error value is calculated as the average over all communication hops $E = \frac{1}{M} \sum_{i=1}^{M} E_i$. M indicates the maximum number of communication hops.

Negative Error: A negative error means that we estimate a larger value for $h(n)$ than it must be. Figure 1(a) illustrates a simple example for a one-dimensional network. The left most node illustrates the seed and the gray scale colors show the different communication hops h_i.



(a) (b)

Fig. 1. An illustrative example for a negative error (a) and a positive error (b)

The error occurs in the communication hop h_2 due to the gap in h_1. The error value in hop 2 is $E_2 = -\frac{1}{4}$. A similar but more fatal error occurs when the gap between two nodes is higher than the communication radius. Here, the node has no connection to nodes with lower hop count and therefore adapts its hop count to the neighbors with larger hop count values. The negative error dynamically changes in mobile networks as the gaps between nodes vary.

Positive Error: By introducing mobility, a node does not know, if it has moved, therefore, every node has to make sure that it updates its hop count value constantly. When a node with small hop count moves away from the seed into a communication hop with a larger hop count value, the nodes with larger hop count values can reduce their hop counts before the moved node has adapted itself to the new environment due to asynchronous computation throughout the network. This phenomenon helps to reduce the negative error, by causing a counteracting positive error. Figure 1(b) illustrates this positive error. In this example, the positive error happens in the communication hop h_3 with $E_3 = 1$. A drawback of mobility is that the error values can change from negative to positive values, thereby underestimating the distance to the seed. Nevertheless, even without realizing when a node has moved, the natural overestimation of distances can be corrected as an emerging effect of delayed computation and mobility.

V. Experiments

In the experiments, a mobile ad hoc network is simulated where a GA is initiated from one static node. The hop counts are measured for each node and averaged over each communication hop as described in Section IV. Different experiments are conducted using the mobility models presented in III.

We select a 2-dimensional rectangular environment of size 1.0 x 1.0 units with 1000 nodes. The nodes are positioned in the environment using a random uniform distribution. The seed node is placed in the top-left corner. The communication radius r is set to 0.07 units, corresponding to an average neighborhood size of 14 which is close to the critical minimum average neighborhood of 15 for the distance estimation [14]. Based on the size of the environment and the value of the radius, we can have at most 21 communication hops. In the experiments, we measure the error for 100 cycles. In one cycle, 1000 random nodes are executed, i. e., they first update their hop count and then move with the probability of $p_m = 0, 0.1, 0.3, 0.5, 0.7, 1.0$. The simulation environment is designed as a torus world, i. e., nodes can leave the environment and enter again at the opposite side. When a node leaves the environment, its hop count is set to $unknown$, simulating a new node entering the environment. For all movements the allowed speed is selected randomly between $\frac{r}{2} - 0.001$ units per cycle and $\frac{r}{2} + 0.001$ units per cycle. This way, a node requires at least two cycles to leave its own communication radius. For RW, the maximum distance to move is selected as 0.6 units and maximum cycles to move is set to 10. In both RD and RWP a move is paused for 10 cycles. For GM α is set to 0.75 and an average angle of 0 degree measured from the bottom border of the environment is selected. Angle tolerance

TABLE I
ERROR E IN DIFFERENT COMMUNICATION HOPS h_i IN A STATIC NETWORK

i	1	2	3	4	5	6	7
E_i	0	-0.4	-0.6	-0.9	-1.1	-1.4	-1.7
i	8	9	10	11	12	13	14
E_i	-1.8	-2.1	-2.3	-2.5	-2.8	-3	-3.2
i	15	16	17	18	19	20	21
E_i	-3.3	-3.5	-3.7	-3.8	-4	-4.1	-3.6

for BR is set to 30 degrees. In the ColM, there are 10 leaders that are each followed by 10 nodes and the angle tolerance for StrM is set to 30 degrees.

A. Error in Static Network

The first experiment concerns measuring the error value E_i for the 21 communication hops in a static network. The results are shown in table I. We obtain only negative values which intensify with increasing communication hop. This confirms the negative error model in Section IV. For further investigation only the middle hops (10-15) are considered as they contain a relatively high and similar number of nodes.

B. Mobile Network

In order to analyze the effects of mobility on the negative error, the RW individual mobility scheme is considered under different movement probabilities p_m and compared to the results in static network (Figure 2). We select RW as representative, since in preliminary experiments similar behaviors were observed for the other movements and RW is one of the most studied mobilities in literature. The negative error from the static network is reduced and with $p_m = 0.5$, the error rate is very close to zero. The mobility rate of 0.7 already changes the error towards positive values and with a probability of 1.0, the effect of a positive error is clearly observable.

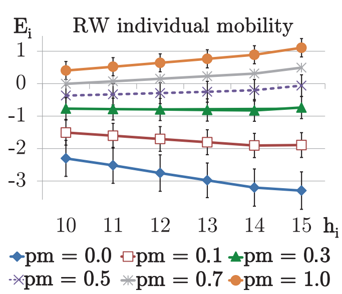


Fig. 2. Error in communication hops when adding mobility

As $p_m = 0.5$ shows the lowest error values, we further analyze the other presented mobility models with this probability rate.

1) Influence of individual mobilities: Figure 3 shows the average error for the individual mobility models except for RWP as it has a high negative error. This is due to the fact that all of the nodes basically move in the middle of the field and after some cycles the network loses contact to the seed and the error drastically decreases (Figure 4). As one can see, all the individual mobility models overcome the negative error

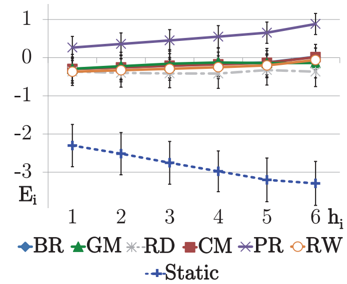


Fig. 3. Error with different individual mobility schemes

of a static network. Furthermore, the error is quite constantly near zero for all five communication hops. This shows that the compensation of positive and negative error works for each hop independently. This is an important observation that guarantees an improvement in a hop count derived distance estimation. When looking at Figure 3, PR shows a noticeable higher positive error than the other mobility models which can be explained by the character of this model as all nodes are moved away from the seed. As a positive error can only occur with movements in the opposite direction of the seed, the positive error introduced by this move is higher than when using other mobility schemes.

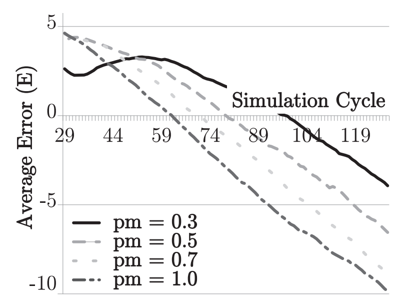


Fig. 4. RWP movement over time

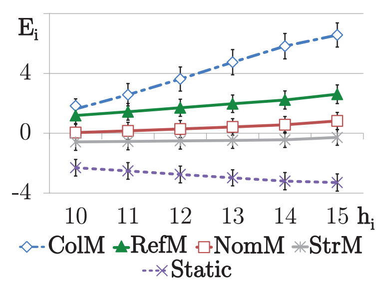


Fig. 5. Error with different group mobility schemes

Besides, BR, GM, CM, RD, and RW show very similar behavior in terms of error values. RD exhibits a slightly more negative behavior due to the pauses the nodes take as they come along the borders. This reduces the mobility over the observed period of time which is accompanied by a reduced positive error influence.

From these results, we conclude that the error rate of GA can be reduced in scenarios with independent individual movements. Our experiments reveal that positive error does not get dominant with a probability of $p_m = 0.5$ unless the movements mostly lead away from the seed. Furthermore, a criterion was identified that implies whether a network lost its connection to the seed as in this case the negative error drifts to infinity. This criterion can even be monitored in each node in a decentralized way when knowing that the network has a more or less stable size. Additionally, it has been demonstrated that the relation between moving and updating the hop count influences the error compensation and that it is crucial to find the right balance.

2) Influence of group mobilities: Figure 5 shows the computed error values for the group mobility models. The StrM model was designed to simulate similar movements within neighborhoods, therefore, the adaptations the nodes have to make to the hop counts are also similar. This seems to have a positive effect on the error as can be seen in Figure 5. The same observation can be made with NomM. As one group moves together through the network the error seems to be less volatile. As already shown for the PR another important factor is the direction of a move relative to the seed. Both in the StrM and the NomM, the groups move quite randomly through the network. The mixture of movements leading away or towards the seed leads to less positive error as for example in ColM. Here, the groups keep moving in more or less the same direction. Next to the ColM, the RefM shows a high positive error. This can be explained by the additional movement introduced by moving the reference point network as well as each node individually. The examined group mobility models confirm the observation that the direction of the movements influence the error rate in a network. Moreover, the results for the RefM indicate that speed might be an important factor for the level of positive error that arises through mobility.

VI. Conclusion and Future Work

This paper is about an experimental analysis of different error models for GA in ad hoc networks. The goal is to obtain an understanding of the hop count distribution in the presence of different mobility models. The hop count error reflects the variance in the length of one hop count in a MANET due to node distribution, mobility or density. The experiments and analysis indicate that with mobility of low rates, the error can be reduced, whereas a high degree of mobility as well as certain characteristics, such as the direction of the movements with respect to the seed as well as the relative movement of neighbors, can lead to an overcompensation of the naturally negative error. This discovery can be used to dynamically adapt the estimation of one hop length depending on the speed of the respective node, leading to an improvement in localization accuracy for mobile nodes. In future work, a speed dependent hop count based distance estimation is to be developed.

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