Energy Constrained Positioning in Mobile Wireless Ad hoc and Sensor Networks

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Abstract

The positioning of wireless nodes has been an active research area over the last decade. Many network positioning algorithms have been proposed to solve this problem. The vast majority assume that a fixed set of nodes (called seeds) have a mechanism to position themselves at all times (using GPS or other means). The other nodes estimate their positions based on positional information exchanged between nodes using wireless communication. The monetary cost of a GPS unit is decreasing so systems where most nodes are equipped with a GPS unit is foreseeable. A problem with this assumption is that the task of self-positioning via a GPS unit is expensive in terms of energy consumption which results in faster battery decay. In this paper, we assume that every node is capable of self-positioning but activates that module selectively. This allows for balancing the energy costs of self-positioning among all nodes and results in reduced positional error. We investigate several different strategies for governing the self-positioning module and report on their performance.

1. Introduction

A lot of research effort has gone into the problem of positioning, or the estimation of the geographical positions of wireless nodes in ad hoc and sensor networks. The position information is used in many parts of the network infrastructure, including topology maintenance, medium access control (MAC) protocols and routing protocols like geographic routing [1], event localization, target tracking and sensed data mapping. Many algorithms have been proposed to solve this problem in different scenarios.

Most algorithms estimate node positions in a global co-ordinate system. For this, they have to assume that a fixed set of nodes (called seed nodes) have some mechanism to position themselves at all times. One such mechanism is GPS. The other nodes estimate their positions based on positional information of other nodes obtained using wireless communication. This is sometimes called network positioning.

It has also been reported that the extra hardware modules attached to sensors to enable self-positioning often consume significant energy and results in faster battery draining for seed nodes [2]. In recent years,
the monetary cost and size of self-positioning hardware has decreased enough that equipping all sensors with these modules is becoming less prohibitive.

In this paper, we assume that every node is capable of self-positioning but governs the use of that module by activation and deactivation to conserve battery capacity. While one can come up with several simple, intuitive strategies for activation, it is far from clear how these strategies perform.

We investigate several different activation strategies for duty cycling the self-positioning module using simulations and report their performance. Specifically, we show that effective duty cycling strategies not only save energy but can reduce the mean positional error.

There is a tradeoff between battery power consumed in self-positioning and the positional error achieved. Higher numbers of seeds decrease the positional error and increase the energy consumption, and vice versa.

1.1. Related Work

There have been several papers on the energy cost of positioning in different types of wireless networks. Several papers (e.g., [3, 4, 5]) have focused on GPS duty-cycling schemes for cellular telephones. Wu et al [3] used spatio-temporal correlations in GPS signals to come up with an adaptive duty-cycling scheme. Constandache et al [4] uses heuristics and mobility predictions to maximize the positional accuracy for a given energy budget. Paek et al [5] store historical information about where GPS is not known to work well (e.g. urban areas) and use bluetooth and a duty-cycled accelerometer to compute location uncertainty.

Tilak et al [6] used various predictive mobility models and computed the frequency of positioning required to maintain a maximum positional error. Several papers ([7, 8]) have looked at duty-cycling for tracking applications using predictive mobility models. Chan et al [9] utilized multiple radios and a clustering of nodes to increase the positional accuracy of WI-FI enabled nodes.

None of these strategies are appropriate for ad hoc and sensor networks. Not every node has multiple radios or good accelerometers and the computational and battery capacities are far more limited than those of modern cellular phones, especially smartphones.

Our work is most similar to [10, 11] in that it uses a positioning algorithm to estimate positions from available positional information and only switches on the self-positioning module. However, this paper differs from Jurdak et al [10, 11] in two important respects: first, we investigate the effect of duty cycling on far more sophisticated (and range-free) algorithms compared to them, and second, we do not use predictive mobility models.

The literature on positioning algorithms is extensive and we refer the interested reader to the surveys [12, 13]. Here we mention a few papers relevant to this work. Several very good positioning algorithms have been proposed over the last decade. The seminal paper by Hu and Evans [14] proposed an algorithm called MCL that produced good positional accuracy in sensor networks with mobile nodes. This kicked off a series of papers [15, 16, 17, 18] that all increased the positional accuracy, often without significant increase in computation or communication costs. All of these algorithms utilized the available location information very efficiently to greatly reduce positional error.

1.2. Organization of Paper

The models which are used to study the tradeoff between energy usage and positional error are presented in Section 2. The positioning algorithm and the activation strategies are described in Section 3. The performance of the activation strategies is given in Section 4 while Section 5 gives some concluding remarks.

2. System Model

The work in this paper considers a system of battery operated computing devices that are capable of wireless communication. Each device is located in an environment and communicates with nearby nodes via the exchange of messages. The devices are mobile so the position of a sensor can change over time. The model describes the environment, wireless communication and mobility of the devices. The dynamics of the system of devices are captured in discrete time steps. In each time step a node can communicate, perform some computation, and change its location.
The devices are represented by a set of $n$ nodes $V = \{u_1, \ldots, u_n\}$ and a two-dimensional Euclidean space $\mathbb{R}^2$ models the environment in which the devices reside. The embedding $p_i : V \rightarrow \mathbb{R}^2$ gives the position of each node at a point in time $t$, and the distance $d(p_i(u_i), p_j(u_j))$ between $u_i$ and $u_j$ is the Euclidean distance.

The communication region of a node is the set of positions in $\mathbb{R}^2$ where a transmitted message can be received by another node. This paper uses the unit disk model of communication where the communication region of a node $u$ by a disk of radius $r$ about its position $p_i(u_i)$. Any node $u_j$ that is positioned within the disk is connected to node $u_i$. The set of nodes that can receive a message from node $u_i$ at time $t$ are called first neighbours, denoted $N_i(u_i, 1)$. The set of nodes outside $N_i(u_i, 1)$ that can receive a message from any node in $N_i(u_i, 1)$ are referred to as second neighbours and are denoted $N_i(u_i, 2)$.

The positions of the nodes change over time. The random waypoint mobility model is used to describe node movement. Under this model each node selects a destination point from the space $\mathbb{R}^2$ and moves along a line towards it. In each time step the node moves a random distance chosen uniformly from the interval $[0, \delta]$ on this line. When the node reaches the destination it selects a new destination point for the next time step. This model has been used extensively in previous work [19, 20].

The communication range $r$ and the maximum movement distance per time step $\delta$ are known to each node. A connectivity-based positioning algorithm takes as input the connectivity information from each time step and computes a position estimate $q_i(u_i)$ for a node $u_i$. Due to node mobility, a distributed form of the connectivity-based algorithm is considered where nodes use neighbourhood connectivity as input to the positioning algorithm to limit processing delays and energy consumption caused multi-hop communication. The positioning algorithm is executed on each node and the connectivity graph is learned through the exchange of messages between nodes. The positional error of a node at time $t$ is $d(p_i(u_i), q_i(u_i))$, and is a measure of performance of a positioning algorithm which is widely used in the literature [17, 21, 22, 23].

In addition to the standard hardware, each node is equipped with a GPS unit that can determine its position. The term 'GPS' is used as a moniker throughout this paper to denote an auxiliary positioning system or self-positioning system. The standard system model traditionally assumed small number of nodes are equipped with a GPS unit that is always active [24, 25, 17]. These nodes are referred to as a seed nodes and always know their true positions. The model used in this paper deviates from this assumption by including a GPS unit in each node however the unit is not always active.

3. Energy Constrained Network Positioning for Mobile Nodes

The nodes in the system under consideration are mobile so their position is always changing which necessitates periodic position estimation. Each node in the system is equipped with a GPS unit that can be activated and deactivated at the discretion of the node. When a GPS unit at a node $u_i$ is activated it provides the node with its position $p_i(u_i)$ but consumes a large amount of energy. When a GPS unit is deactivated a node relies on a network positioning algorithm to estimate its position. The objective of this work is to investigate strategies that balance the use of the GPS unit with the need to conserve energy. An existing network positioning algorithm called WMCL-B is amended with several GPS activation strategies that govern the use of the GPS unit. This algorithm was selected because it is one of the best mobile positioning algorithms and it is easily extended. The positioning algorithm is briefly described in Section 3.1 and three GPS activation strategies are described in Section 3.2

3.1. Positioning Algorithm

The WMCL-B positioning algorithm uses local connectivity information to impose constraints on the position of a node. The basis for the constraints are the communication range $r$ and the node speed $\delta$. Figure 1a illustrates a set of connectivity constraints imposed a node’s position. The constraints imposed on a node’s past position can be adjusted to restrict the possibilities for the node’s current position at time $t$.

A sample-based positioning scheme uses a set of sample points to approximate the set of possible positions for a node that satisfy all constraints. The sample-based approach provides a very flexible and efficient basis for a positioning algorithm. The WMCL-B positioning algorithm is an implementation of this sampling process [17]. For complete details readers are referred to the original paper.

The general sampling process for a node $u_i$ at time $t$: 

Fig. 1: An illustration of the general process for sample-based positioning algorithms. Figure 1a shows the constraints, geometrically realized as circles, imposed on the position of node $u_1$ by its first neighbour nodes $u_2 \ldots u_3 \in N_1(u_1, 1)$ and a second neighbour node $u_5 \in N_2(u_1, 2)$. The grey region represents the set of positions that satisfy the constraints. The solid circle represents the communication region of range $r$ and the dashed circle represents the constraint adjusted for positional error. Node $u_5$ has a contracted constraint because it is not a first neighbour of $u_1$. The positions of the sample points $S_t$ in the sample box are shown Figure 1b and the remaining sample points after filtering is shown in Figure 1c.

1. Construct sample box $B_t$ using the constraints on the node’s position.
2. Draw a set $S_t$ of sample points from the sample box $B_t$.
3. Remove all infeasible sample points from $S_t$ that do not satisfy all constraints.
4. Estimate position $q_t(u_i)$ using the centroid of the remaining sample points.

Figure 1 illustrates some of these steps. All connectivity-based positioning algorithms that use the sample point approach follow these steps. The WMCL-B algorithm also estimates its positional error using the boundary of the sample box.

During the communication phase each node broadcasts a message containing the identification and positional information about itself and its neighbours. This phase allows each node to learn of the local connectivity information and positional information.

A small adjustment was made to the WMCL-B algorithm to accommodate the activation and deactivation of a node’s GPS unit. If node $u_i$ activates its GPS unit in time $t$ it knows its position $p_t(u_i)$. To preserve this positional information the node creates a single sample point at point $p_t(u_i)$. This adjustment allows the node to use the positional information acquired from the GPS activation in later time steps.

### 3.2. Activation Strategies

A GPS activation strategy is a component of a positioning algorithm and determines when a node’s GPS unit is active. If a GPS unit is active a node knows its position. Three activation strategies have been formulated for this work: fixed, random and error. The activation strategy is integrated into the positioning algorithm operating on each node.

The **fixed** strategy uses a predefined subset of the nodes that are capable of using their GPS unit. This strategy is identical to the one that is used in most positioning algorithms proposed for mobile systems [26, 17, 27, 28]. The strategy is augmented with a duty cycling parameter $c$ that determines the number of time steps between activations of the GPS unit. This parameter is used to regulate the amount of energy usage over time. The fixed strategy is denoted $S_f(c)$.

The **random** strategy activates the GPS unit on a given node with probability $p$ in each time step $t$ and is denoted $S_r(p)$. The expected number of nodes with active GPS units in a time step is $\sum_{i=1}^n p$. The GPS unit is deactivated at the beginning of each time step.
Many positioning algorithms estimate the error of their position estimates. The random strategy is simple but it does not use any positional information. The error strategy, denoted \( S_e(b) \), was developed to take advantage of positional information available to a node that could improve the overall performance of a positioning algorithm. The strategy has single parameter \( b \) that is a threshold on error. In each time step a node determines if its estimated positional error exceeds the error threshold \( b \). In the event the positional error exceeds the threshold and the node has the largest positional error when compared to its first and second neighbour nodes, the GPS unit at the node is activated. The GPS unit is deactivated at the beginning of each time step. The basis for this strategy is to improve positional error in regions with high positional error and limit the number of activations in a local region of the network.

Intuitively one would expect the performance of the positioning algorithm when operating with the random GPS activation strategy to greatly exceed that of the fixed strategy. This intuition is validated in Section 4. It is noted the fixed activation strategy was not expected to be competitive with the other two strategies but it was included to provide a basis for comparison against the performance of proposed positioning algorithms that use this strategy.

It is assumed a design objective of a network positioning system for mobile nodes is to provide accurate position estimates at a minimum cost. The value of parameters \( p \) and \( b \) of strategies \( S_f(p) \) and \( S_e(b) \) directly influences the number of active GPS units and therefore represents a tradeoff between energy usage and positional error. Section 4 compares the performance of the three strategies in terms of energy usage and positional error.

4. Performance Evaluation

A computer simulation that implements the model described in Section 2 was used to evaluate the GPS activation strategies. The purpose of the evaluation of the strategies is to compare the performance of the three strategies in terms of positional error and energy usage. This paper compares the expected positional error achieved by the positioning algorithm under each strategy for a given amount of energy. The expected positional error is a commonly used performance measurement for reporting the quality of a positioning algorithm. The differences in energy consumption between the strategies due to computation is negligible compared to the requirements of a GPS unit. None of the strategies use extra network communication beyond what is required by the WMCL-B algorithm.

The simulation was conducted on a system of \( n = 80 \) nodes that reside in a field of size \( 1000 \times 1000 \) units. The initial location for each is completely random. The communication range of each node is \( r = 100 \) units. The simulation is executed for 1000 time steps.

Energy consumption is measured by the mean number of GPS activations per time step. Each activation strategy uses the same mean number of GPS activations per time step. The mean number of activations was determined using the \( S_e(\cdot) \) strategy. The mean was used to calculate the parameter values \( c \) and \( p \) for the \( S_f(c) \) and \( S_e(p) \) strategies, respectively. Each strategy is evaluated by the computer simulation for a range of mean GPS activations and node speed values \( \delta = \{20, 40, 60, 80\} \). Table 1 gives the mean number of GPS activations per time step used for all strategies. The figures in the table were derived from the number of activations made by the strategy \( S_e(b) \) for \( b \in \{20, 40, \ldots, 300\} \). The comparison use the same number of GPS activations per time step on average. There are 60 data points (mean positional error) for each strategy.

The strategy \( S_e(\cdot) \) depends on an estimate of positional error which is undefined at time step \( t = 1 \). To fairly compare each of the strategies, nodes \( u_1, u_2, \) and \( u_3 \) activate their GPS units to initialize the positioning system in time step \( t = 1 \). The GPS units are deactivated in the next time step and the chosen strategy is executed thereafter.

The computer simulation uses the same software as the authors of WMCL-B [17]. The WMCL-B positioning algorithm was modified with the changes described in Section 3.1, so that positional information obtained from a GPS activation is retained in the form of a sample point.

4.1. Comparison of Activation Strategies

In general the measure for comparison of two activation strategies \( S_A(\cdot) \) and \( S_B(\cdot) \) is given by
Table 1: The mean number of GPS activations per time step used for all activation strategies. The values were determined based on the mean number of GPS activations for a given error threshold $b$. The positional error over time is related to node speed $\delta$ so a range of activations was determined for different node speeds.

<table>
<thead>
<tr>
<th>Error Threshold $b$</th>
<th>Maximum Node Speed $\delta$</th>
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<tr>
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<td>20</td>
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<td>20</td>
<td>10.28</td>
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<td>40</td>
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<tr>
<td>280</td>
<td>0.52</td>
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<tr>
<td>300</td>
<td>0.41</td>
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</table>

The improvement in mean positional error of strategy $S_r(\cdot)$ over strategy $S_f(\cdot)$ is shown in Figure 2. The results confirm the intuition: the random activation strategy produces a substantial improvement in mean positional error. This is due to the ease with which positional information acquired from the GPS can be spread over the network. The $S_f(\cdot)$ strategy becomes more competitive when the number of GPS activations is increased because the graph distance from nodes with inactive GPS units to nodes with active GPS units is decreasing.

4.2. When to Activate the GPS

The improvement in mean positional error of strategy $S_e(\cdot)$ over strategy $S_r(\cdot)$ is shown in Figure 3. It is noteworthy that the strategy $S_e(\cdot)$ is superior to the random strategy in all instances. The $S_e(\cdot)$ strategy performs best compared to $S_r(\cdot)$ when the node speed is low and an appropriate threshold is used. As the node speed increases the positional error grows dramatically with node speed. The $S_e(\cdot)$ and $S_r(\cdot)$ can respond to the increasing positional error by activating more GPS units.

When the node speed $\delta$ is lower the positions of the nodes are changing slowly which causes the change in error with respect to time to be lower. Therefore when the node speed $\delta$ is low and the error threshold $b$ is high it can take many time steps before a GPS unit is activated.

The error threshold parameter $b$ for the $S_e(\cdot)$ strategy should be chosen carefully to balance the trade-off between energy consumption and the mean positional error. Figure 4a plots the mean positional error achieved for the positioning algorithm operating under the $S_e(\cdot)$ strategy for a range of node speeds. Figure 4b plots the mean number of activated GPS units per time step for the same strategy. There is little benefit to choosing an error threshold $b \leq 100$ since there is no change in the mean positional error and the reduction in GPS activations is quite small. When $b > 100$ the positional error starts to increase and the number of GPS activations starts to decrease quickly. It is the region above a threshold of 100 where a tradeoff between energy usage and positional error occurs. It is notable that the rate of change in energy usage is greater than the rate of change in the positional error in the intermediate region.
Fig. 2: The fractional improvement in positional error that the random strategy $S_r(\cdot)$ achieves over the fixed strategy $S_f(\cdot)$. The improvement diminishes as the maximum node speed $\delta$ increases. The advantage of random activation of GPS units decreases as the mean number of GPS units per time step increases.

Fig. 3: The fractional improvement in positional error that the error strategy $S_e(\cdot)$ achieves over the random strategy $S_r(\cdot)$. The evaluation reveals that, for a given amount of energy, a 10% – 20% reduction in mean positional error is achieved when strategy $S_e(\cdot)$ is used over strategy $S_r(\cdot)$.
5. Conclusion

This paper considers the problem managing the tradeoff between energy usage and positional error for positioning algorithms. The use of GPS improves positional error as the cost of greater energy consumption. Three strategies for governing the use of a node’s GPS unit were proposed: fixed, random, and error. A computer simulation was used to conduct a variety of experiments at different node speeds and different GPS activation levels to compare the performance of the activation strategies in terms of positional error.

The error activation strategy depends on estimated positional error and is superior to both the random activation and the fix activation strategies. The use of positional error information in the decision for GPS activation is important. The error strategy achieves significant reduction in positional error over the random strategy using the same amount of energy in all comparisons.

The decision to activate a node’s GPS unit depends on node speed and causes a tradeoff between decrease in error and increase in energy use with greater activation. There is a level of GPS activation above which further activations do not result in decreases in the mean positional error. An avenue for future work on this problem would investigate the optimal value on the error threshold.

References


