Localization Method for Mobile Wireless Sensor Networks based on Motion Model with Temporal Dependency

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Abstract

In many applications, apart from sensed data, the location information of the deployed sensor node is also desirable as it can be used to improve routing efficiency. Hence, the discovery of the locations or positions of sensor nodes is one of the most critical issues for WSNs. Localization is the process of determining the absolute or relative physical location of a specific node or the target node. Mobility would appear to make localization more difficult. 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. In this paper, we introduce mobility model with temporal dependency to replace the random mobility model. Simulation results show that it can reduce the estimation error.

Keywords

Localization, Mobile Wireless Sensor Networks, Spat.

1. Introduction

A wireless sensor network (WSN) consists of tiny sensor nodes equipped with computational, communication, and sensing capabilities, whereby each sensor node can collect data about the environment, such as temperature, vibration levels, light, electromagnetic strength, and humidity. The sensed data is then transmitted to the sink node through a chain of multiple intermediate nodes that help forward the data. Due to their capabilities and versatility, WSNs have been widely used in many areas, such as military affairs, healthcare, and environmental monitoring. In many applications, apart from sensed data, the location information of the deployed sensor node is also desirable as it can be used to improve routing efficiency. Hence, the discovery of the locations or positions of sensor nodes is one of the most critical issues for WSNs.

Localization is the process of determining the absolute or relative physical location of a specific node or the target node. Although a global positioning system (GPS) [1] can provide precise location information, the costly hardware and large size make it unsuitable for WSNs. Furthermore, a GPS can only be used outdoors since it depends on signals directly received from satellites for localization. Besides the GPS, numerous localization methods [2–13] have also been proposed. But none of them consider mobile nodes and seeds. Although mobility would appear to make localization more difficult, in paper [14] Hu introduced the sequential Monte Carlo Localization method and argued that it can exploit mobility to improve the accuracy and precision of localization. In this work, they 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.

In this paper, we introduce mobility model with temporal dependency to replace the random mobility model. Simulation results show that it can reduce the estimation error.

2. Related Works

The existing work on localization falls into two main categories: range-based and range-free localization.

Range-free approaches, such as Centroid [15], APIT [16], and DV-HOP [17], mainly rely on connectivity measurements (for example, hop count) from landmarks to the other nodes. Since the quality of localization is easily affected by node density and network conditions, range-free approaches typically provide imprecise estimation of node locations.

Range-based approaches measure the Euclidean distances among the nodes with certain ranging techniques and locate the nodes using geometric methods, such as TOA [18], TDOA [19], [20], and AOA [21]. All those approaches require extra hardware support.

RSSI-based range measurements are easy to implement and are popular in practice. Empirical models of signal propagation are constructed to convert RSSI to distance [22]. The accuracy of such conversions, however, is sensitive to channel noise, interference, and multipath effects. Moreover, when there are a limited number of landmarks, range-based approaches have to undergo iterative calculation processes to locate all the nodes, suffering significant accumulative errors [23]. More recent proposals mainly focus on the issue of error control and management [24], [25]. Liu et al. [26] propose iterative localization with error management. Only a portion of nodes are selected into localization, based on their relative contribution to the localization accuracy, so as to avoid error accumulation during the iterations. Similarly, Kung et al. [27] propose to assign different weights to range measurements with different nodes and adopt a robust statistical technique to tolerate outliers of range measurements [28].

A range-free approach beyond connectivity is proposed in [29]. The signature distance is proposed as a measure of the Euclidean distance between a pair of nodes. In order to address the issue of no uniform deployment, the authors further propose regulated signature distance (RSD), which takes node density into account. Based on the comparison among nodes' neighbor sequences, RSD is quantified. This approach needs to be integrated with a certain existing localization approach to function.

Differing with most of the existing approaches, CDL is a combination of range-free and range-based schemes. It can independently localize a WSN. CDL addresses the issue of no uniform deployment with virtual-hop localization (Section IV-A). Utilizing the information of estimated node locations, RSSI readings, and network connectivity, CDL filters good nodes from bad ones with two techniques (Section IV-B), namely neighborhood hop-count matching and neighborhood sequence matching. CDL pursues better ranging quality (namely more accurate reference locations and more accurate ranging) throughout the localization process. This is the most significant characteristic of CDL that distinguishes it from existing approaches.

3. Localization Method based on Motion Model with Temporal Dependency

Mobility of a node may be constrained and limited by the physical laws of acceleration, velocity and rate of change of direction. Hence, the current velocity of a mobile node may depend on its previous velocity. Thus the velocities of single node at different time slots are 'correlated'. We call this mobility characteristic the Temporal Dependency of velocity.

However, the memoryless nature of Random Walk model, Random Waypoint model and other variants render them inadequate to capture this temporal dependency behavior. As a result, various mobility models considering temporal dependency are proposed.

The Gauss-Markov Mobility Model was first introduced by Liang and Haas [30] and widely utilized[31]. In this model, the velocity of mobile node is assumed to be correlated over time and modeled as a Gauss-Markov stochastic process.

For simplicity, we consider the two-dimensional space. The mobile localization problem can be stated in a state space form as follows. Let t be the discrete time, $l_t(x_t, y_t)$ 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 $p\left(l_t \middle| l_{t-1}\right)$ describes the prediction of node's current position based on previous position, and an observation equation $p\left(l_t \middle| o_t\right)$ 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 $p\left(l_t \middle| o_0, o_1, ..., o_t\right)$. 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} and o_t.

In a two-dimensional simulation field, the Gauss-Markov stochastic process can be represented by the following equations.

$$\begin{cases} v_t^x = \alpha v_{t-1}^x + (1-\alpha)\upsilon^x + \sigma^x \sqrt{1-\alpha^2} w_{t-1}^x \\ v_t^y = \alpha v_{t-1}^y + (1-\alpha)\upsilon^y + \sigma^y \sqrt{1-\alpha^2} w_{t-1}^y \end{cases} \quad (1)$$

Where $V_t = \left[v_t^x, v_t^y\right]^T$ is the the velocity vector at time t and time t-1 and $V_{t-1} = \left[v_{t-1}^x, v_{t-1}^y\right]^T$ is the velocity vector at time t-1 and time t-2. υ^x and υ^y is the average motion vectors in x and y directions respectively.

w_{t-1}^x and w_{t-1}^y are the uncorrelated random Gaussian process with mean 0 and variance σ^x, that is to say

$$f\left(\omega_{t-1}^x\right) = \frac{1}{\sqrt{2\pi}\sigma^x} \exp\left[-\frac{\left(\omega_{t-1}^x\right)^2}{2\left(\sigma^x\right)^2}\right] \quad (2)$$

$$f\left(\omega_{t-1}^y\right) = \frac{1}{\sqrt{2\pi}\sigma^y} \exp\left[-\frac{\left(\omega_{t-1}^y\right)^2}{2\left(\sigma^y\right)^2}\right] \quad (3)$$

When the node is going to travel beyond the boundaries of the simulation field, the direction of movement is forced to flip 180 degree. This way, the nodes remain away from the boundary of simulation field.

The Gauss-Markov model is a temporally dependent mobility model whereas the degree of dependency is determined by the memory level parameter α. α is a parameter to reflect the randomness of Gauss-Markov process. By tuning this parameter, Liang and Haas [13] state that this model is capable of duplicating different kinds of mobility behaviors in various scenarios:

1. If the Gauss-Markov Model is memoryless, i.e. α=0. The Eq.(1) is

$$\begin{cases} v_t^x = \upsilon^x + \sigma^x w_{t-1}^x \\ v_t^y = \upsilon^y + \sigma^y w_{t-1}^y \end{cases} \quad (4)$$

Where the velocity of mobile node at time slot t is only determined by the fixed drift velocity $\bar{\upsilon} = [\upsilon^x, \upsilon^y]^T$ and the Gaussian random variable $\bar{W}_{t-1} = [w_{t-1}^x, w_{t-1}^y]^T$. Obviously, the model described in Eq.(4) is the Random Walk model.

2. If the Gauss-Markov Model has strong memory, i.e.,α=1. The Eq.(1) is

$$\begin{cases} v_t^x = v_{t-1}^x \\ v_t^y = v_{t-1}^y \end{cases} \quad (5)$$

where the velocity of mobile node at time slot t is exactly same as its previous velocity. In the nomenclature of vehicular traffic theory, this model is called as fluid flow model. This time slot t mobile node motion vector is saying before the motion vector is the same.

$l_{t-1}\left(x^{i}{}_{t-1}, y^{i}{}_{t-1}\right)$ is a possible location at time t-1, L_{t-1} is the set of possible locations at time t-1. For each sample, we can use this new mobility model to get a new sample $l_t\left(x^{i}{}_{t}, y^{i}{}_{t}\right)$. The new sample set L_t is produced.

$$\begin{cases} x_t^i = x_{t-1}^i + v_t^x \\ y_t^i = y_{t-1}^i + v_t^y \end{cases} \tag{6}$$

We can get a new possible location $l_t\left(x^{i}{}_{t}, y^{i}{}_{t}\right)$ by put (1) into (6)

$$\begin{cases} x_t^i = x_{t-1}^i + \alpha v_{t-1}^x + (1-\alpha)\upsilon^x + \sigma^x\sqrt{1-\alpha^2}\,w_{t-1}^x \\ y_t^i = y_{t-1}^i + \alpha v_{t-1}^y + (1-\alpha)\upsilon^y + \sigma^y\sqrt{1-\alpha^2}\,w_{t-1}^y \end{cases} \tag{7}$$

4. Simulation

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 (Vmax, Vmin, Smax, Smin). We represent the speed as the moving distance per time unit. A node's speed is randomly chosen from [Vmin, Vmax]; a seed's speed is randomly chosen from [Smin, Smax]. We consider the impact of speeds on both accuracy and convergence time.

We compare the localization results based on motion model with temporal dependency with that based on random waypoint mobility model. 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.

From the simulation results, we can see that the localization results based on motion model with temporal dependency has lower estimation error and smaller convergence time.

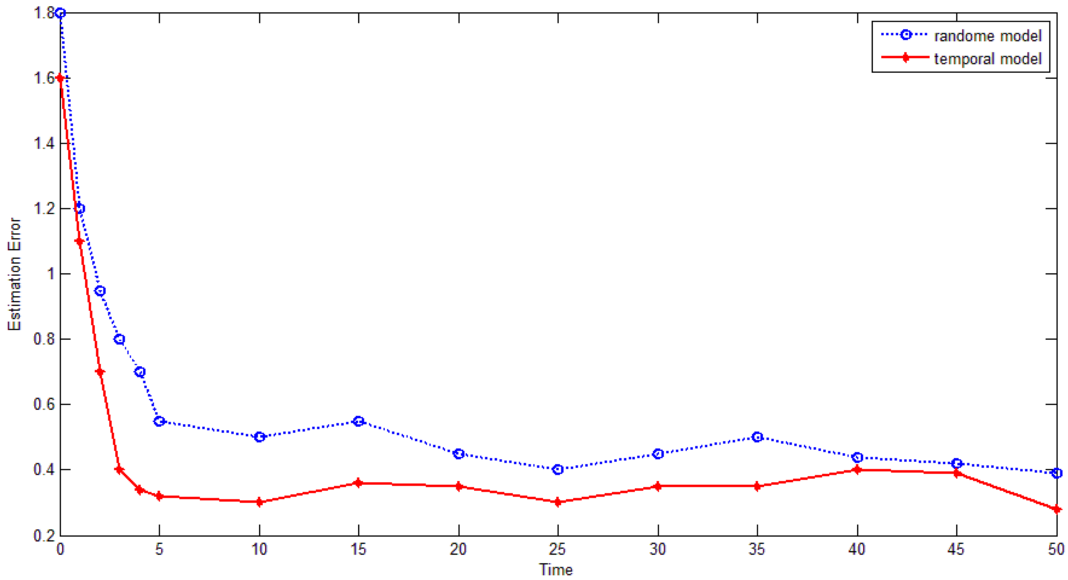

Fig. 1 estimation error of localization method based on two mobility model

5. Summary

The discovery of the locations or positions of sensor nodes is one of the most critical issues for WSNs. Localization is the process of determining the absolute or relative physical location of a specific node or the target node. Mobility would appear to make localization more difficult. 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. In this paper, we introduce mobility model with temporal dependency to replace the random mobility model. Simulation results show that it can reduce the estimation error.

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