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A DISTRIBUTED LOCALIZATION METHOD FOR MOBILE WIRELESS SENSOR NETWORKS

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ABSTRACT
Mobile wireless sensor nodes need to know their locations in many applications; otherwise the data from the nodes is meaningless. In this paper, we study a special case and propose a distributed localization method for mobile wireless sensor networks. In the case, a part of nodes are randomly selected as mobile nodes and their moving directions and ranges are randomly selected. Every node knows its original location. The mobile nodes record their moving directions and ranges by the equipped sensors to calculate their positions. Then every mobile node's localization is refined by the optimization algorithm, which is based on the difference between the measured distances and estimated distances with its still neighbors. Finally, simulation results are provided to evaluate the proposed method.

KEY WORDS
Sensor networks, localization, optimization, simulations.

1. Introduction

With the recent development in network technology and micro-electro-mechanical systems (MEMS), it is possible that wireless sensor networks are increasingly applied in many fields, such as environmental monitoring, target tracking, object search and rescue, medical application, and military surveillance, etc. The ability of a sensor node to determine its physical location is of fundamental importance in wireless sensor networks (WSNs) [1]. The global position system (GPS) is the most prevalent positioning device. However, it is not feasible to equip each node with GPS capability due to costs, node's limited power and constraints in locations that do not have the direct line-of-sight to the satellites [2]. In recent years, there are a lot of researches on nodes' localization in WSNs.

In the stationary WSNs, the nodes are still so it doesn't need to calculate the nodes' locations iteratively. There are mainly two types of methods to localization: range-based and range-free. In range-based methods, sensor nodes measure the distances or angels through time of arrival (TOA) [3], time difference of arrival (TDOA) [4], received signal strength indicator (RSSI) [5], or angle of arrival (AOA). For example, in [6], DV-distance method is proposed to estimate 1-hop average distance, which is used to calculate the nodes' locations. [7] provides a novel localization approach based on multi-dimensional scaling (MDS). In range-free methods, sensor nodes don't need the measurement. For example, DV-hop [6] estimates 1-hop average distance by the anchors' distances and hops. APIT [8] method computes the centroid of a related polygon as a node's location. The range-based methods are more precise than the range-free ones, though they need some kinds of measurement techniques.

In the mobile WSNs, the nodes are moving and the network topology is changing, so a localization method should be used to calculate the nodes' locations quickly and iteratively. The Monte Carlo method [9] is a basic approach to solve the localization problem in mobile WSNs, which contains three steps: initialization, sampling and re-sampling. There are several improved approaches based on the Monte Carlo method, such as MSL and MSL*[10], MCB [11], Dual and Mixture [12] and so on. These methods rely on the communication between the nodes. Other approaches that are not based on the Monte Carlo method are also developed. In [1], the authors propose a dynamic MDS-based localization algorithm to calculate the mobile nodes' locations by adding some virtual nodes to increase the nodes' density. In [13], a history of anchor information is used to characterize the mobility of mobile nodes. The unknown node then calculates its location with the archived anchor using a regression model.

The Monte Carlo methods predict the node's next location using the mobility model, and then refine the prediction by the node's neighbors' information. Without measuring the distances between the nodes, these methods are simple and distributed; however, the predication can only provide an area of the node's location, so the positioning error is large.

Due to the mobility of the nodes, the localization method should be simple and distributed. Most methods for localization need anchors, which know their positions anytime by GPS or human intervention. The accuracy of these methods is related to the density and deployment of anchors. When a node doesn't have an anchor neighbor, it has to communicate to its n-hop nodes, which is consuming and ineffective. In this paper, a distributed localization method is developed without anchors for mobile wireless sensor networks. The main idea is to refine the mobile nodes' localizations by the optimization algorithm. This paper is organized as follows: in section 2, we introduce the studied case and the devices used by the proposed method. Section 3 presents the detail of the distributed localization method. The simulations and evaluation are given in section 4. Section 5 concludes the paper.

2. A Case of Mobile Sensor Networks

In the studied case, all the nodes are randomly distributed in a limited area and know their original locations. The time is divided into mobile and localization discrete period. They are alternate and continuous. In the mobile period, a part of nodes are randomly selected as mobile ones and they can move in any direction (0-2π) within a limited range. There are no anchors in the network and every node only needs to communicate with its neighbors.

Each node is equipped with accelerometer, ranging sensor and compass. The accelerometer and compass are used to record the node's moving range and direction in once mobile period. The ranging sensor measures the distances between the mobile node and its still neighbors. There are mainly three techniques to measure the distance between two nodes. RSSI technique measures the received strength of signal to estimate the distance. TOA technique records the time of the signal arriving and calculates the distance between two nodes by multiplying the signal's speed. TDOA technique records the time of the signal sending and returning to calculate two nodes' distance. The ranging errors of TOA and TDOA are smaller than the RSSI's, but more complex. Without loss of generality, we will compare the localization results in different ranging error in the simulations.

3. Distributed Localization Method

The time is divided into mobile and localization discrete period. We assume that the mobile node's moving direction doesn't change in one mobile period. When a mobile node stops moving, it estimates its location based on the data of the compass and accelerometer. Meanwhile, the node measures the distances with its still neighbors and receives their coordinates to refine the estimation of its location.

3.1 Mobile period

In the mobile period, a part of nodes are randomly selected as mobile ones and can move within a limited range in any direction (0-2π). The maximum of the movement distance is the half of the communication radius.

3.2 Localization period

Once a mobile node stops moving, it will locate itself based on the previous location and its neighbors' information. The proposed method contains two steps: estimation and refinement. The following is the detail of the two steps.

3.2.1 Estimation

The mobile node calculates its location based on the previous location and the sensors' data as shown in Fig. 1. d is the moving radius of the mobile node and θ is the angle between the moving direction and the *x*-axis. (x_1, y_1) is the previous location of the node. So the current coordinate (x_2, y_2) can be calculated in (1).

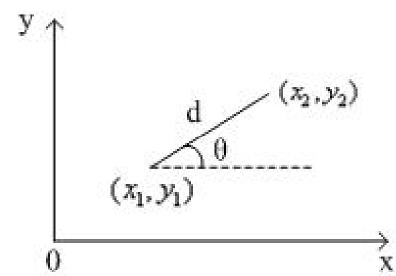

Figure 1. Localizing a node based on sensors' data

$$\begin{cases} x_2 = x_1 + d \cdot \cos\theta \\ y_2 = y_1 + d \cdot \sin\theta \end{cases} \tag{1}$$

(x_2, y_2) is the estimation of the node's location. It is affected easily by the sensors' measure errors. The estimation error will become larger as the localization times increasing. In order to keep the estimation error in a small scale, the mobile node's location must be refined through the optimization algorithm.

3.2.2 Refinement

The objective function is defined in (2). i represents the mobile node and j is i 's still neighbor. Let f_i is

$$f_i = \sum_{j}^{N_i} (d_{ij} - p_{ij})^2 \tag{2}$$

Tthe function for the mobile node i ; N_i denotes the number of i 's still neighbors; d_{ij} is the Euclidean distance measured by the distance sensor; p_{ij} denotes the estimated distance calculated by the nodes' coordinates in (3).

$$p_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{3}$$

The objective of the refinement is to minimize f_i to make the estimated distances conform to the measured distances as shown in (4). The gradient descent method is

$$\min \sum_{j}^{N_i} (d_{ij} - p_{ij})^2 \tag{4}$$

used to realize the objective in (5). (Δ_x, Δ_y) are the coefficients of the refinement. They can be fixed or be

$$\begin{cases} x_i(k+1) = x_i(k) + \dfrac{\partial f_i}{\partial x_i}\Delta_x \\ y_i(k+1) = y_i(k) + \dfrac{\partial f_i}{\partial y_i}\Delta_y \end{cases} \tag{5}$$

alterable with the objective function changing. Anyhow, the coefficients must make f_i be decreasing. If (Δ_x, Δ_y) are defined as (6), the method in (5) is the most speedy to satisfy the formulation (4). After the step of

$$(\Delta_x, \Delta_y) = \left(-\frac{\partial^2 f_i}{\partial {x_i}^2}, -\frac{\partial^2 f_i}{\partial {y_i}^2}\right)\cdot\alpha \tag{6}$$

refinement, $(\hat{x}_i, \hat{y}_i)$ is the mobile node's estimated coordinate.

Unlike the previous localization algorithms, the proposed method is able to locate the nodes without anchors and available in some conditions, such as underwater or underground. Each mobile node locates itself using the sensors' data and its still neighbors' information. So the method is distributed and simple.

4. Simulations

The performance of the proposed method is analyzed in this section. The running simulations are in Matlab 7.0.

4.1 Simulation parameters

The proposed method doesn't require anchors but all nodes' original locations must be known. In the simulations, all of the nodes have the same communication radius. There are 100 nodes randomly deployed in an area $10r \times 10r$. Each node's communication radius is R_c and the biggest moving radius for each mobile node is the half of R_c . In the mobile period, each mobile node randomly selected its moving direction from 0 to 2π and the movement distance in $[0.25R_c,\ 0.5R_c]$. The absolute positioning error $Error_{ab}$ is computed in (7). The relative error $Error_{re}$ is defined in (8), which is the ratio of $Error_{ab}$ to the length of the mobile node's path.

$$Error_{ab} = \frac{\sum_{i=1}^{N} \lVert (x_i, y_i)_{real} - (\hat{x}_i, \hat{y}_i)_{est} \rVert}{N} \tag{7}$$

$$Error_{re} = \frac{Error_{ab}}{Path\ Length\ of\ The\ Node} \tag{8}$$

In order to reduce the computational cost, (4) is converted to (9). When f_i 's variation is less than ε , the

$$f_i(k) - f_i(k+1) < \varepsilon \tag{9}$$

refinement should stop because f_i 's variation is so small that the refinement is not necessary. In our simulations, ε takes the value of 0.01.

4.2 Simulation results

In the simulations, let DE denote the ranging error of the ranging sensor; ME denotes the measuring error of the compass and accelerometer; RN denotes the ratio of the mobile nodes to all the nodes; NM denotes the method without optimization and OM stands for the method with optimization. r takes the value of 10 in all experiments.

Fig.2 shows the comparison of the localization results

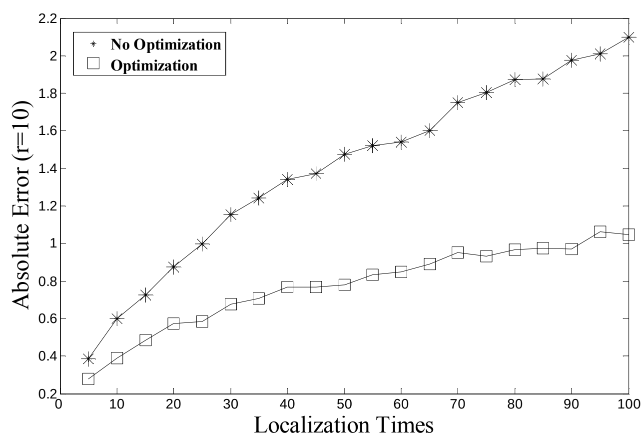

Figure 2. Absolute error of the localization results

of NM and OM. In the simulation, , DE=5%, ME=5%,RN=30% and $R_c = r$. It's clear that adding optimization can improve the node's localization precision. The mean positioning errors of OM and NM are 1.05 and 2.09 respectively when the localization times are 100. As the localization times increasing, the absolute positioning errors are enlarging because the current coordinate is calculated based on the previous one and the error accumulates gradually.

Fig.3 shows the relative error corresponding to the absolute error in Fig.2. As the localization times increasing, the path length of the mobile node is growing but the relative errors of NM and OM are decrease. When the localization times are 90, the relative error of NM is

2% and OM's is 1%. That means the node moves 100 meters while the positioning errors are 2 and 1 meters for NM and OM.

In Fig.4, $R_c = 1.5r$, ME=10%, RN=30%. DE takes the

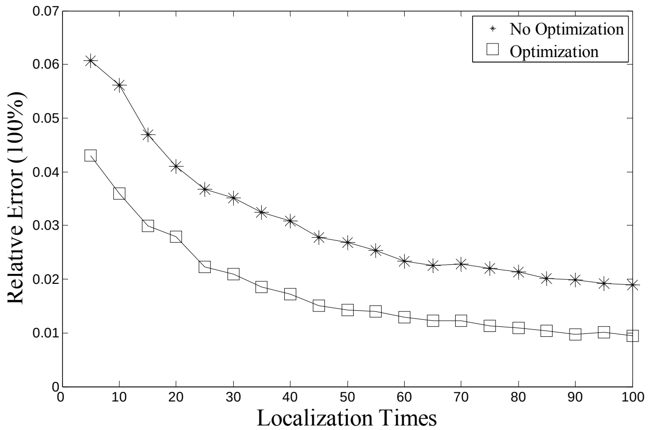

Figure 3. Relative error of localization results

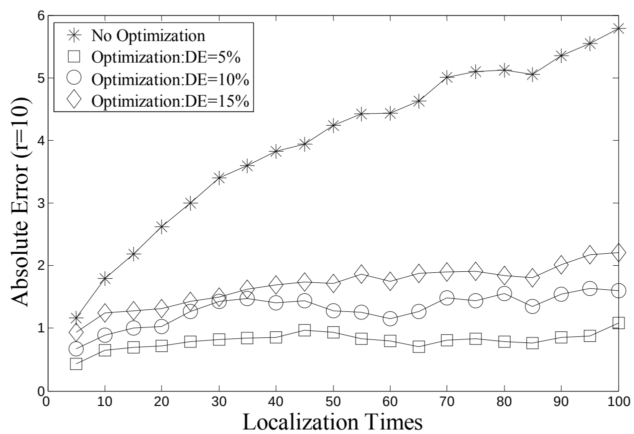

Figure 4. Comparison of the localization results in different DE

value of 5%, 10% and 15%. When R_c becomes larger, the node's movement distance is increasing, so the positioning error of NM grows a lot. When DE is increasing, the distances between the mobile node and its still neighbors, which are used to do the refinement, are less precise. As shown in Fig.4, when the localization times are 80, the positioning error of NM is 5.12 and the OM's positioning errors are 0.79 (DE = 5%), 1.55 (DE = 10%) and 1.84 (DE = 15%). As the localization times increasing, the gradient of the OM's curve is less than that of the NM's.

When RN is increasing, the positioning error is growing. As shown in Fig.5, when the localization times are 50, the node's positioning error of OM is 9.04, which will influence the optimization effect. For investigating the influence of the connectivity on the positioning error, the maximum of the movement distance is fixed to $0.8r$. Fig.5 displays the localization errors in different connectivity, in which DE=10%, ME=10%, RN=50% and R_c takes the value of r, $1.5r$ and $2r$. The connectivity of the network is 2.8, 6.1 and 10.3 respectively.

The bigger connectivity means the mobile node has more still neighbors as references when it refines its location, so the positioning precise is higher. As shown in Fig.5, when the localization times are 80, the positioning error of NM is 10.15 and the OM's positioning errors are 4.86 (connectivity=2.8), 3.39 (connectivity = 6.1) and 2.29 (connectivity = 10.3).

Fig.6 compares the localization results in different DE, in which $R_c = 1.5r$, ME=10%, RN=50%. As DE increasing, the positioning error of OM is enlarging. When localization times are 80, the positioning error of NM is 5.89 and the OM's errors are 2.06 (DE = 5%), 3.06 (DE = 10%) and 5.09 (DE = 15%).

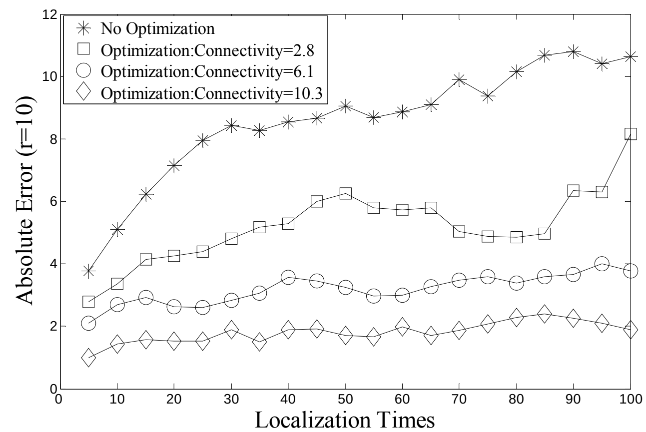

Figure 5. Comparison of the localization results in different connectivity

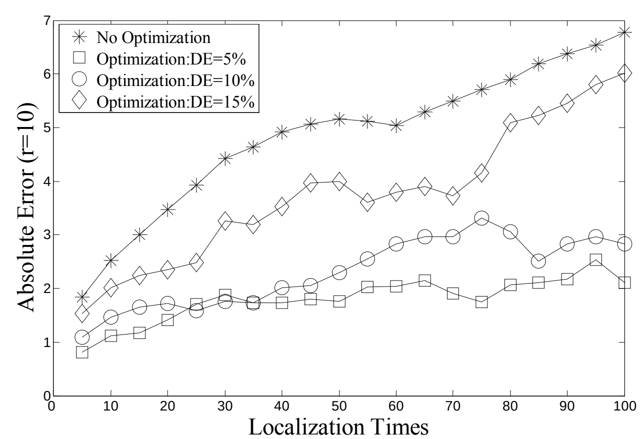

Figure 6. Comparison of the localization results in different DE

Fig.7 and Fig.8 show the comparison of the localization results when RN is 80%. The number of the still nodes is small so the refinement doesn't performs as well as the described above. Fig.7 compares the performance of OM in different connectivity, in which DE=10%, ME=10%, and the connectivity takes the value of 6.1, 9.5 and 15.5. As the connectivity increasing, there are more neighbors used to do the refinement for the

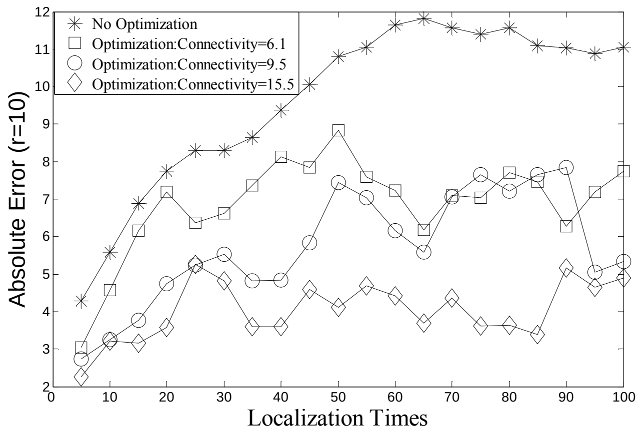

Figure 7. RN=80%, Comparison of the localization results in different connectivity

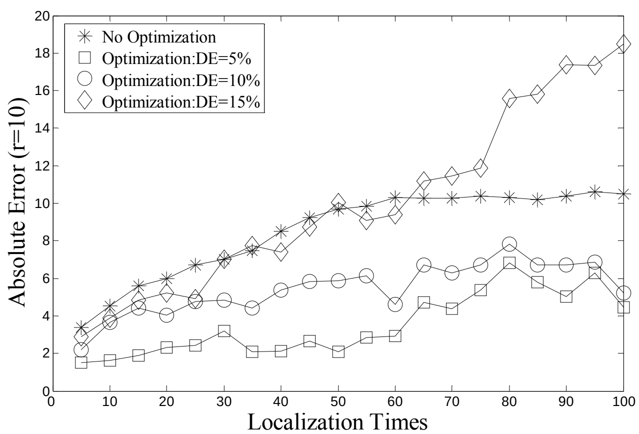

Figure 8. RN=80%, Comparison of the localization results in different DE

mobile nodes, so the positioning error decreases. When the localization times are 80, the positioning error of NM is 11.57 and the OM's positioning errors are 7.72 (connectivity = 6.1), 7.22 (connectivity =9.5) and 3.64 (connectivity = 15.5).

Fig.8 displays the localization results as DE is increasing, in which $R_c = 2.5r$ and ME=10%. When DE=15%, the refinement makes the positioning precise worse. However, when DE=5% or 10%, the refinement can still decrease the positioning error.

The refinement is affected by the nodes' location estimation calculated in (1) and the measurement distances between the mobile node and its still neighbors. If the errors of the two variables are large, the refinement doesn't work, as shown DE=15% in Fig.8.

5. Conclusion

In this paper, we propose a distributed localization method for mobile wireless sensor networks. This method contains two steps: estimation and refinement. Firstly, the mobile nodes locate themselves based on their previous locations and the sensors' data. Then they will use the still neighbors' information to refine the locations calculated above. The simulations show that the refinement can improve the positioning precise unless the sensors' measurement errors are large. This method works without anchors, which is able to locate the nodes underwater or underground. Every node only needs communicate with its neighbors. When the localization times are increasing, it can keep the positioning error in a small scale. The simulation results show the performance of the proposed method in different situations.

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