Autonomous Localization Method in Wireless Sensor Networks

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Abstract

In wireless sensor networks, localization systems use data from sensors which receive signals from moving targets, measure RSSI, and translate RSSI into the distance between sensor and target. We consider a localization system that gives an error measurement model of distance and introduce a relationship between the number of data and accuracy. Extending the lifetime of a system is needed to save the energy of sensors and collect the necessary data. In this paper, we propose an efficient data collecting technique to get the accuracy required for the applications while saving energy. We verify that our proposal can efficiently collect necessary data to get accuracy in cases of random sensor placement.

1. Introduction

Recent advances in wireless communications and electronics have enabled the development of microsensors that can manage wireless communication and that also have calculation power. By deploying a large number of sensors, wireless sensor networks can monitor large areas and be applied in a variety of fields, such as monitoring environment, the air, the water, and the soil). Also, sensor networks can offer sensing data to context-aware applications which can adapt to user situations in ubiquitous computing. If properly conducted, sensor nodes can work autonomously to measure temperature, humidity, luminosity and so on. Sensor nodes send sensing data to the sink node which has been deployed for data collection [1].

In the future, sensors will be cheaper and deployed everywhere; services which depend on user location and localization of sensors will become more important. GPS [8] is a popular location estimation system, but since it needs signals from GPS satellites, it cannot work indoors [6]. Using sensor networks instead of GPS makes indoor localization possible [6]. In the future, we expect that applications will increase that satisfy location information requirements, such as navigation systems and target tracking systems in office buildings or locations in supermarkets, etc. Sensor location is important too, because sensing data without knowing the sensor location is meaningless in environmental sensing applications such as water quality monitoring, seismic intensity, and indoor air quality, and so on [11, 13].

Methods using ultrasound or lasers realize high accuracy; however, each device adds to the size, cost, and energy requirements. For those reasons, such methods are not suitable for sensor networks. An inexpensive RF-based approach with low configuration requirements was researched. But the Receive Signal Strength Indicator (RSSI) has larger error because it is subject to the deleterious effects of fading channels [11]. RSSI needs more data to achieve high accuracy than other methods. However, collecting a large amount of data causes an increase in traffic and sensors' energy consumption and decreases the lifetime of sensor networks. Furthermore, increasing the time to collect data has a bad influence on real-time operation to get location information.

In this paper we propose a localization system that estimates the position of moving targets by using RSSI in sensor networks. Accuracy depends on the number of data, measurement error, and a localization algorithm. We show the relationship between error of position estimation and the number of data about position estimation using RSSI and MMSE (explained in Section 3). Our results will show that estimation error is not proportionate to the number of data. Accordingly we attempt to collect only the necessary data to get the required accuracy. To reduce the data collected by the sink and extend the lifetime of sensor networks, we propose a data collection technique in which sensors recognizes the number of surrounding sensors. They autonomously decide whether to send sensing data and work in random deployment of sensors. It does not need centralized control, complicated calculations, or the sending of a lot of packets. In simulations we evaluate the effectiveness of our proposed technique.

The remainder of this paper is organized as follows. In Section 2, we explain related work. In Section 3, we explain our model of localization systems. In Section 4, we show the relationship between the number of sensors and accuracy and describe the problem. In Section 5, we describe our proposed data collecting technique and its evaluation. We conclude this paper and mention future work in Section 6.

2. Related work

Indoor localization systems have already been proposed. First, the RADAR system needs RSSI measurements of various points in a research area to make a signal strength map [2]. Users can estimate user location by searching for the nearest RSSI points on a map. Location estimation accuracy depends on a map and how many points RSSI has measured. Calamari system [16] has also adopted a distance measurement technique by RSSI. Range errors upwards of 10% have been reported in [16], usually after a fairly involved calibration step that estimates the path loss parameters and adjusts for variations in transceiver characteristics. Ref. [13] uses ultrasound devices to estimate sensor location. It shows how density networks can resolve sensor position. This system can resolve the position of sensors if they do not move. But the range of ultrasound is very short, only about 3m. Ref [14] is also aimed at the system which adopted the distance measurement system by ultrasound whose effective range is 5m. These system work only in dense sensor networks. Ref. [11] shows a radio channel fading model and proposes an RF-based Quantized RSS (QRSS) measurement. QRSS is less expensive than RSSI, but we could not verify its performance because it does not show how to calculate the measurement data. Ref. [10] evaluates the performance of localization systems using RSSI and Time of Arrival (TOA) in such actual environments as parking lots and offices with partitions, desks, and computers. Both methods can work in actual environments. Ref. [4] presents a time-based positioning scheme (TPS) in outdoor sensor networks. TPS relies on Time-Difference of Arrival (TDoA) of RF signals measured locally at a sensor to detect range differences from the sensor to three base stations. Beacon placement has also been researched [3]. A beacon is a node which knows its position. Localization accuracy differs according to placement plan, grid and randomness. Results show that a grid is a good placement plan, but suggest that it depends on a localization algorithm. Ref [12] presents a method by which a sensor node can determine its location by listening to wireless transmissions from three or more fixed beacon nodes. This system is based on an Angle of Arrival (AoA) estimation technique, and needs special antenna configrations.

Furthermore, some researches which perform localization take into consideration not only the data of distance but topological information up exist. Multidimensional scaling (MDS) is one of such the techniques [15, 7]. MDS uses connectivity information to derive the locations of the nodes in the network, and can take advantage of additional data, such as estimated distances between neighbors oe beacons. Ref. [5] provides a theoretical foundation for network localization in terms of graph rigidity theory. Ref. [9] took in this idea and have proposed a robust distributed algorithm under noisy range measurements. Our subject for research is a system by which many sensors are installed fixed and the position is known. We consider a system which carries out sensing of the position of the target which can move under such environment. Therefore, a system which takes into consideration the geographical position and the connection relations between nodes shall not be made into the object of this paper. However, when a small number of sensor needs to perform position detection, it is thought that the approach using such topological information may become important.

3. Localization system model

We consider a system in which sensors estimate the position of targets in an observation area. The target has a wireless device and sends a packet for position estimation. For multiple targets, a packet includes a target ID. After receiving a packet, sensors measure RSS and transform RSS into distance. Sensors send sensing data to the sink which calculates the target position from sensing data. We also consider the following details about localization systems:

- Sensor placement
  We assume that all sensors have already been deployed and that they do not move. Sensors are assumed to know their position for position estimation. There are two ways to learn sensor position. First, a manager registers a sensor position to the sink's database. If sensors need to know their position, the sink sends sensor position to resolve position when only a few sensors (or a sensor) are placed on a grid. But it cannot resolve the problem when a lot of sensors are placed randomly. Second, a manager places a few beacon nodes which know their position, and sensor nodes estimate their position to use information from a beacon node [13]. Beacons can handle a lot of sensors placed randomly.

- Data collection
  Sensors receive packets from targets, measure the power of the packet, and transform RSS into distance to use theoretical and empirical models. The packet includes a target ID and a packet number. After reading the packet, a sensor gets a target ID, a packet number,

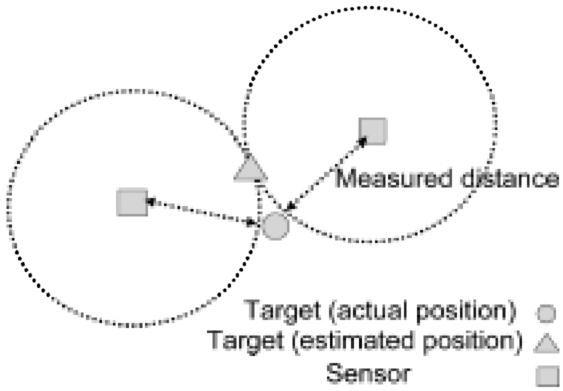


Figure 1. Localization Algorithm: ML Multilateration

and a distance between sensor and target. And then the sensor sends the following data: its ID, the target ID, packet number, and distance between sensor and target to the sink.

- Calculation at the sink
  We use a Maximum Likelihood (ML) estimation [13] that estimates the position of a target by minimizing the differences between the measured and estimated distance (Figure 1).

  ML estimation of a target's position can be obtained by Minimum Mean Square Error (MMSE) [13]. MMSE can resolve the position from data including error for calculating a target's position. We explain calculation for a two-dimensional case. MMSE needs more than three sensors to resolve a target's position. First, the sink searches for the same data in terms of a target ID and a packet number from collecting data from sensors. The difference between measured and estimated distances is defined as Eq. (1) below.

$$f_i(x_0, y_0) = d_i - \sqrt{(x_i - x_0)^2 + (y_i - y_0)^2} \quad (1)$$

  x_0 and y_0 is the unknown position of the target node, x_i and y_i for $i = 1, 2, 3...N$ is the sensor position, and N is the total number of data which the sink has collected. d_i is a distance between sensor i and a target. The target's position x_0 and y_0 can obtained by MMSE. Eq. (2) is obtained by setting $f_i = 0$, squaring and rearranging.

$$-x_i^2 - y_i^2 + d_i^2 = (x_0^2 + y_0^2) + x_0(-2x_i) + y_0(-2y_i) \quad (2)$$

  After getting Eq. (2), we can eliminate the $(x_0^2 + y_0^2)$ terms by subtracting kth equation from the rest.

$$-x_i^2 - y_i^2 + d_i^2 - (-x_k^2 - y_k^2 + d_k^2) = 2x_0(x_k - x_i) + 2y_0(y_k - y_i) \quad (3)$$

  Eq. (3) transforms Eq. (4), which can be solved using matrix solution given by Eq. (5). Position (x_0,y_0) be obtained by calculating Eq.(5).

$$y = Xb \quad (4)$$
$$b = (X^T X)^{-1} X^T y \quad (5)$$

  where

$$X = \begin{bmatrix} 2(x_k - x_1) & 2(y_k - y_1) \\ \vdots & \vdots \\ 2(x_k - x_{k-1}) & 2(y_k - x_{y-1}) \end{bmatrix} \quad (6)$$

$$y = \begin{bmatrix} -x_1^2 - y_1^2 + d_1^2 - (-x_k^2 - y_k^2 + d_k^2) \\ \vdots \\ -x_{k-1}^2 - y_{k-1}^2 + d_{k-1}^2 - (-x_k^2 - y_k^2 + d_k^2) \end{bmatrix} \quad (7)$$

$$b = \begin{bmatrix} x_0 \\ y_0 \end{bmatrix} \quad (8)$$

4. Evaluation of localization system performance

4.1. Error Model

RSSI measurement, which is influenced by the effects of channel fading, varies by multipath and individual differences of antenna and power of senders. We introduce three error models to simulate a localization system and determine the relationship between data and accuracy. These models assume uniform distribution of the measurement error. If target's position estimates in permissible error in case of uniform distribution, we expect the system to work in case of other distribution and real environment, because uniform distribution has a larger variation than other distributions such as normal distribution.

(1) Measurement error is in proportion to the distance between the sensor and the target. A mean of the absolute value is 10% of distance , for example, if distance between a sensor and a target is 10m, measurement error is given as a random value between -2m and 2m. This model follows the experiment in [13].

(2) Measurement error is independent of distance and the mean of the absolute value is 1m. This is based on the assumption that sensors near the target do not always measure the precise effects of such obstacles.

(3) This follows the upper boundaries of both the above two models. If a system can manage such a large error model, it's no exaggeration to say that it is free of measurement error.

4.2. Simulation results

In our simulation, we generate target at random in simulation area which is a square 100m on each side. Sensors receive the packet from the target within 20m and send data to the sink. Figures 2(a) and 2(b) show the mean localization error for various numbers of sensors. In error model (2), the mean estimated error is smaller than models (1) and (3). In error model (1), measurement error of sensor near the target is the smallest of the three, but the mean estimated error is about the same as error model (3). In models (1) and (3), the data of sensors far from the target have large error and are a bad influence on localization. The localization error is disproportionate to the number of sensors, but the number of collected data is in proportion to the number of sensors.

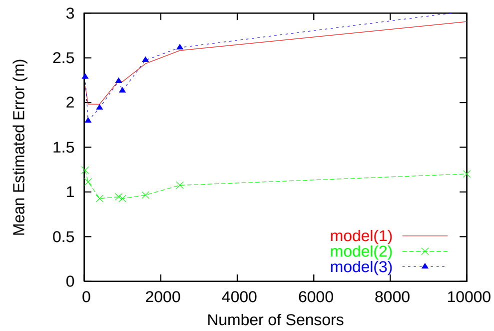
It is a problem that sensor networks consume large amounts of energy when collecting much data, but the improvement of localization accuracy is small. Two reasons can be considered. First, MMSE does not need so much data. Second, sensors far from the target have large errors, and in a large number of sensors, the sink collects more data from far sensors than in a small number of sensors. To save energy and get highly accurate data, we propose a mechanism in the next section, where sensors decide whether to send sensing data.

5. Data collecting technique

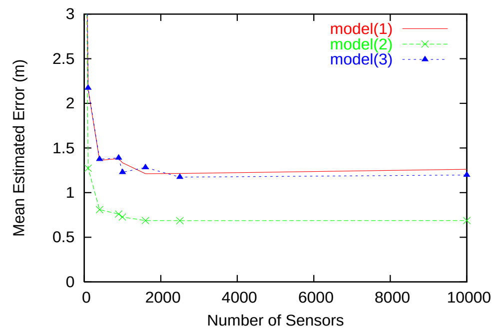
5.1. Relationship between accuracy and the number of data

First, we verify the relation between the number of data and position estimation accuracy by limiting the amount of data used in calculation. In simulation, sensors do not send data without a certain distance from the target. Figure 3 shows the relation between the restriction distance from a target and position estimation error in case of 1000 sensors deployed in the simulation area. Models (2) and (3) show large error when distance is short, because larger measurement error than model (1) and collected data are too small to estimate precisely. In case measurement error is large, much data need to accurate estimation. In the case of models (1) and (3), there exists an optimal value of the restriction distance which makes estimated error the minimum. On the other hand, in the case of model (2), it turns out that an error becomes small in proportion to the amount of data, so that measurement error is independent of distance, unlike the other models, but we can define an optimal distance by demands of an application, i.e. longtime or accurate operation. Results show that localization system can cut down the number of data collected.

When sensors are distributed uniformly, it is thought that the method of controlling the number of sensors by distance



(a) Grid deployment



(b) Random deployment

Figure 2. Mean localization error vs. number of sensors

is effective. However, such a method cannot be applied in biased placement of sensors. We next propose a data collecting technique, which can be used in biased placement.

5.2. Proposed technique

Since the propagation characteristic changes greatly with environment, it is necessary to determine the number of data which is needed in order to acquire a certain accuracy in the environment where it actually works. Users can decide the number of data to collect by prior knowledge and inform all sensors by flooding from the sink. Targets can inform sensors of the number of data by sending packets, too. If accuracy is less than required by applications, users can easily increase the data to be collected, because this mechanism can always change the number of data to be collected.

In our proposal, whether sensors send data depends on the density around the sensor and the distance between the sensor and the target. Sensors send data if the distance between the sensor and the target is shorter than a certain distance which is calculated by each sensor. Sensors measure density by receiving packets sent for information of existence at each period of time and measuring communication

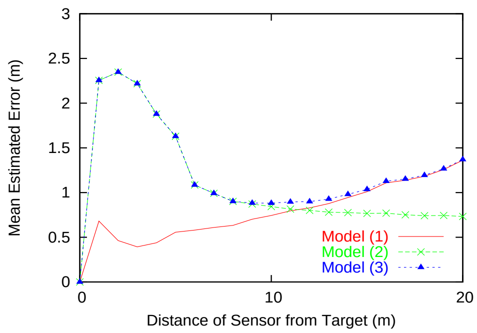


Figure 3. Mean localization error vs. distance which sensor send data within

range. Density around sensor i is approximately determined by Eq. (9). R is communication range, M_i is the number of sensors within R form sensor i.

$$Density = \frac{M_i}{\pi R^2} \tag{9}$$

We define the number of data required by the system by Z. Sensor i sends data if the measured distance is shorter than distance D_i to collect Z. The number of sensors within D_i is proportional to density and D_i is defined in Eq. (10).

$$\frac{M_i}{\pi R^2} = \frac{Z}{\pi D_i^2} \tag{10}$$

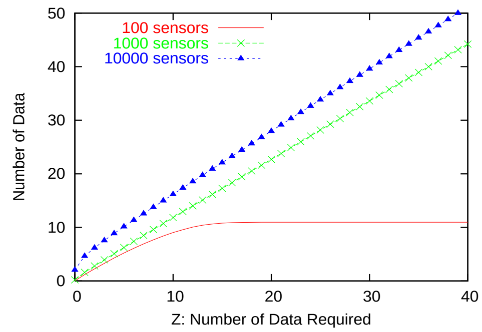
Arranging Eq. (10), Eq. (11) is obtained.

$$D_i = R\sqrt{\frac{Z}{M_i}} \tag{11}$$

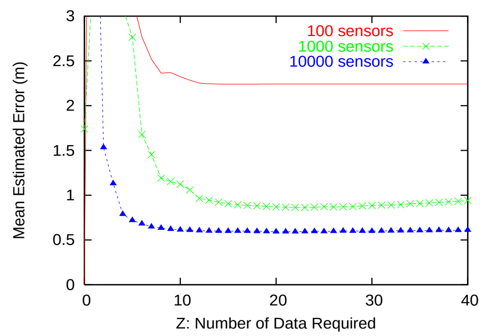
D_i depends on density around sensor i. The sink can collect the same amount of data independent of sensor deployment density, because if the density around sensor i is high, D_i is small and if the density around sensor i is low, D_i is high.

5.3. Performance evaluation

We validate our proposed data collecting technique in this subsection. Our simulation model is the same as in the previous section. We show the results in error model (3), setting R as 20m and in random placement. Figure 4(a) shows that the proposed technique collects data almost as we intend, but, in case of 100 sensors, sensors around the target number about ten, and for that reason the sink cannot collect more than ten data. The number of data collected was a little more than required, because sensors at the edge of the simulation area underestimate density and unnecessarily send data. The mean estimation error, as shown in Figure 4(b), drops for a large number of sensors, 1000 and 10,000 sensors. Note that the mean estimation error is lower



(a) Mean collected data vs. number of data required



(b) Mean estimation error vs. number of data required

Figure 4. Performance of data collecting Technique

than 1m when Z is 9 for 1000 sensors and when Z is 4 for 10,000 sensors. The proposed technique saves sensor energy and achieves higher localization accuracy than collecting data from all sensors within 20m.

Next we verify the data collecting technique in biased topology. In simulation, we generate 1000 sensors, use error model (3) and compare the technique to data collection with a system which only restricts distance. Simulation area is a square 100m on each side. Biased deployment is 700 sensors deployed in left bottom of the area and the rest are in other parts of the area (see Figure 5). Generating target randomly in the area, proposed technique using ten as the number of data required and collecting from sensors within 8m radius (method in Subsection 4.1) show about the same accuracy. We simulate by generating target in each point (25,25), (25,75), (75,25) and (75,75) in Table 1. Accuracy of two methods is about same at each point, but there is a large difference in amount of data in point (25,25) which is on left bottom in the area and has high density. Proposed technique collects a constant number of data in each

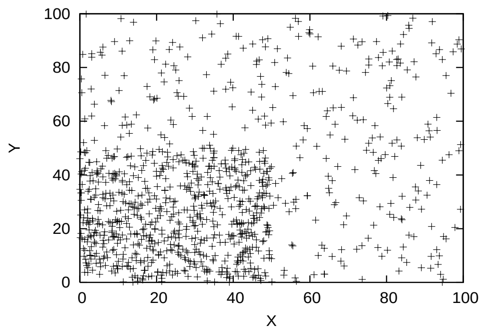


Figure 5. Biased topology of 1000 sensors

Table 1. Comparison between two method

	Proposal system whose number of data is 10		Collecting data from sensors within 8m radius	
	Error	Data	Error	Data
(25,25)	0.982	9.48	0.834	85.64
(25,75)	1.082	10.63	0.901	13.09
(75,25)	0.665	13.05	0.618	16.21
(75,75)	0.818	11.52	0.969	15.11

point and is excellent in terms of saving energy. The results of simulations in this section show proposed technique can collect the required number of data and keep localization accuracy constant in uniform and non-uniform placement of sensors.

6. Conclusion and future work

In this paper, we have presented a localization system that uses RSSI to obtain the distance between sensors and targets for wireless sensor networks. We have discussed the relationship between data, accuracy, and sensor placement. Collecting a small amount of data saves the sensor's battery and extends the lifetime of the sensor network. In simulation results, a large amount of data does not necessarily accomplish high accuracy. We propose and evaluate an Autonomous Localization Method that collects the necessary number of data. It saves sensor's energy and achieves high localization accuracy. In the present simulation experiment, we do not implement the transmission of data packet. We are going to build next a simulation model including the MAC layer protocol in consideration of transmission of a data packet. We will evaluate the delay required in order to collect data using it. Furthermore, our system assumed dense networks and can estimate small error, but its performance was not good in sparse networks. We will consider a mechanism that can obtain a certain degree of accuracy with fewer sensors and save more energy.

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