Cooperative Localization with Pre-Knowledge Using Bayesian Network for Wireless Sensor Networks

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Abstract

Obtaining location information by localization schemes for sensor nodes makes applications of wireless sensor networks (WSNs) more meaningful. Most of localization schemes only use the information gathered during the execution of the localization scheme. In this paper, we proposed a location model based on Bayesian Network [18] with proximity measurement, the deployment information, and the deployment knowledge to describe the relations of the locations of sensor nodes deployed in a grid topology with the probabilistic graphical model. Based on the location model, we present a cooperative localization algorithm, the CLPKBN scheme, to do the localization for a WSN. To evaluate the proposed scheme, we implement the CLPKBN scheme and the Probability Grid scheme on a simulator. The experimental results show that the CLPKBN scheme outperforms the Probability Grid scheme in most of test cases.

1. Introduction

For a WSN application, the power management, sensor deployment, and localization are important issues that need to be dealt with. Among them, the localization issue is essential for most of WSN applications. Without the location information of sensor nodes, the application does not make any sense since we need to know where the event occurred in order to take proper actions. As a result, a localization scheme is needed for sensor nodes to know their locations.

Many localization schemes have been proposed in the literature. In general, they can be classified into two categories, range-based [1][2][3][5][9][12][13][14] and range-free [4][7][11][16][17][19].

In this paper, we want to solve the localization issue for a WSN in which sensor nodes will be deployed as a grid topology. In the above range-free schemes, the Probability Grid scheme [17] is a solution for the problem that we want to solve. However, the Probability Grid scheme uses the hop-count information to reduce the number of anchor nodes used. It needs to get the shortest hop-count to the anchor nodes by flooding the information of the anchor nodes, which costs a lot of networking bandwidth. Also, the accuracy of the locations of sensor nodes obtained by the Probability Grid scheme depends on the deployment of anchor nodes and the number of anchor nodes.

To overcome the drawbacks of the Probability Grid scheme, in this paper, we propose a range-free localization scheme, cooperative localization with pre-knowledge using Bayesian Network (CLPKBN), to achieve high accuracy of locations of sensor nodes without hop-count information and high density of anchor nodes for a WSN. The CLPKBN scheme is based on a location model using the Bayesian Network [18] with proximity measurement, the deployment information (such as grid distance, grid size, etc.), and the deployment knowledge (such as neighbors of a sensor node, the connectivity betweens two sensor nodes, etc.) to describe the relations of the locations of sensor nodes deployed in a grid topology with the probabilistic graphical model. With the proposed localization scheme, a sensor node can act as an anchor node after observing some evidences (such as the location of an anchor/sensor node, etc.). Therefore, we do not need to deploy high density of anchor nodes when we construct a WSN. Instead, we can deploy a few anchor nodes initially. For those sensor nodes that are neighbors of anchor nodes, they can compute their locations based on the locations and the number of neighbors of anchor nodes. Then those neighbors of anchor nodes can act as anchor nodes for their neighbor sensor nodes. This sensor node to anchor node process can be repeated until all sensor nodes compute their locations and the need of the hop-count information can be eliminated.

To evaluate the proposed scheme, we implement the CLPKBN scheme and the Probability Grid scheme [17] on a simulator. Several parameters, including different deployment sizes, different ratio of anchor nodes, different deployment for anchor nodes, different shadowing effects, and different transmission signal power, are used as measurement metrics. From the experimental results obtained from the simulator, the CLPKBN scheme outperforms the Probability Grid scheme in all test cases except the case where the ratio of anchor nodes is set to 0.05.

The rest of this paper is organized as follows. In Section 2, we will present the related work. In the Section 3, we will describe our location model. In Section 4, we will present the CLPKBN scheme in detail. The experiment results of the CLPKBN scheme will be given in Section 5.

2. Related Work

2.1 Range-based schemes

In [1], the authors use the angle of arrival (AOA) to estimate the angle of received signal. They use a set of directional beacon nodes to transmit the signal to the whole network. When the sensor nodes of a network receive the beacon signals, the sensor node evaluates its location by triangulation. This method requires high cost beacon nodes to do the localization.

The GPS [3] uses the time of arrival (TOA) to measure the difference in the time of arrival of signals from several satellites and use the triangulation to infer the position. However, using GPS to locate sensor nodes may not feasible due to cost, energy prohibition, and indoor constraints.

In [2], the time difference of arrival (TDOA) technique is used to estimate the difference time of two sensor nodes. The authors measure the time difference between two simultaneously transmitted radio signal and ultrasound signals. Based on the time difference, the distance of two sensor nodes can be calculated by multiplying the time difference and the speed of sound. The TDOA technique does not depend on the synchronization of the transmitting time of two sensor nodes. Like TOA technique, TDOA relies on additional hardware that is high cost and energy consuming.

The RADAR system [13] uses RSSI technique to estimate the distance to some known landmarks (anchor nodes). It first records the received signal strengths with respect to the landmarks at various locations. It then computes the location of the sensor node by finding the best fit data of the received signal strengths. Since the radio signal strength is unstable and varied under different environments, it is difficult to measure the distance.

2.2 Range-free schemes

In Centroid scheme [11], each sensor node locates itself to the centroid of the anchor nodes that the sensor node can directly communicate with. This scheme is easy to be implemented. The APIT scheme [19] uses anchor nodes to divide a sensing area into triangular regions. A sensor node locates itself according to whether it is inside or outside these triangular regions. Both Centroid and APIT schemes need anchor nodes equipped with powerful radios and a high density of anchor nodes deployment in a WSN to achieve better accuracy of locations.

In DV-Hop scheme [4], each sensor node first tries to find the shortest hop-count to the anchor nodes and estimates the distance to each anchor node by multiplying averaging hop-distance and the hop-count. Then each sensor node uses triangulation to estimate its location. The GRIPHON scheme [7], the Probability Gird scheme [17], and the Amorphous scheme [16] also use hop-count to estimate the distance to the anchor nodes. The GRIPHON scheme is similar to the RADAR system. In the GRIPHON scheme, each sensor node estimates the shortest-hop to the anchor nodes rather than signal strengths. The Probability Grid scheme, in addition to the hop-count information, also exploits the deployment information, such as the grid distance and grid size, to estimate the location of the sensor node accurately. The Amorphous scheme can calculate more accurate hop-distance by assuming that the sensor nodes know the sensor node density of a WSN.

3. Location Model

In this section, we will discuss the location model used in the CLPKBN scheme in details. The location model is a 4-tuple LM = (*DI*, *PK*, *E*, *BR*), where *DI* is a set of deployment information of a WSN, *PK* is a set of pre-knowledge that transformed from *DI*, *E* is a set of evidences that get from run-time, and *BR* is the Bayes rule used to calculate the probabilities of the locations of a sensor node. In the following, we will describe each of them in details.

3.1 Preliminaries

In the following, we will give the definitions used in this paper.

Definition 1: Given a rectangle sensing area AxB, a grid deployment scheme divides the sensing area into MxN grid points where sensor nodes can be placed on. Each grid point g_i is associated with a coordinate ($g_i(x)$, $g_i(y)$), where $g_i(x)$ and $g_i(y)$ are the x-axis and y-axis coordinates of g_i, respectively, $0 < g_i(x) < M$, and $0 < g_i(y) < N$. We call $GS = M$xN the grid size and $GDU = A/M$ (or B/N) the grid distance unit of a deployment scheme.

Definition 2: The distance of two grid points g_i and g_j, denoted as $GD(g_i, g_j)$, is defined as $GDU \times \sqrt{(g_i(x) - g_j(x))^2 + (g_i(y) - g_j(y))^2}$.

Definition 3: The location of sensor node N_a, $Loc(N_a)$, is defined as the coordinate of the grid point g_i wheret N_a is placed on, that is, $Loc(N_a) = (g_i(x), g_i(y))$.

Definition 4: The distance of sensor nodes N_a and N_b, denoted as $Dist(N_a, N_b)$, is define as the distance of their locations, that is, $Dist(N_a, N_b) = GD(g_i, g_j)$, where $Loc(N_a) = g_i$ and $Loc(N_b) = g_j$.

Definition 5: Let S be the set of sensor nodes deployed on a sensing area. Given a sensor node N_a and $Loc(N_a)$, the set of sensor nodes $S - \{N_a\}$ can be partitioned into several disjoint groups, denoted as $S - \{N_a\} = \bigcup_{j=1}^{k} GDist(N_a, d_i)$, according to the distances of sensor nodes in $S - \{N_a\}$ to $Loc(N_a)$, where k is the number of partitioned groups and $GDist(N_a, d_i)$ is the set of sensor nodes whose distance to $Loc(N_a)$ is d_i.

Definition 6: We define $TSP(N_a)$ as the transmission signal power that sensor node N_a used to send a packet out. The default value is 100 for each sensor node.

Definition 7: Two sensor nodes N_a and N_b are connected, denoted as $Conn(N_a, N_b)$, if sensor node N_a can receive the transmission signal from sensor node N_b and vice versa.

Definition 8: Sensor node N_a is a neighbor of sensor node N_b if $Conn(N_a, N_b)$. We use $NEI(Loc(N_a))$ to denote the set of neighbors of sensor node N_a. Then, the number of neighbors of sensor node N_a (or the degree of sensor node N_a) $Deg(N_a) = |NEI(Loc(N_a))|$.

Definition 9: Given $NEI(Loc(N_a))$, $NEI(Loc(N_a))$ can be partitioned into several disjoint groups, $NEI(Loc(N_a)) = \bigcup_{i=1}^{GNEI(Loc(N_a))} GDNEI(N_a, d_i)$, according to the distances of sensor nodes in $NEI(Loc(N_a))$ to $Loc(N_a)$, where $GNEI(Loc(N_a))$ is the number of partitioned groups and $GDNEI(N_a, d_i)$ is the set of sensor nodes whose distance to $Loc(N_a)$ is d_i. Note that $GDNEI(N_a, d_i)$ is a subset of $GDist(N_a, d_i)$.

In the following, we will give notations used in this paper.

Definition 10: We define $NNDL(N_a, N_b, Deg(N_b), Loc(N_b)$ as the message that sensor node N_a received from sensor node N_b. The message contains the information of the number of neighbors and the location of sensor node N_b.

Definition 11: Assume that the probability of sensor node N_c at $Loc(N_c)$ is P_c. We define $KL(N_a, N_b, Loc(N_c), P_c)$ as the message that sensor node N_a gets P_c from its neighbor N_b.

3.2 *DI*

In this paper, we want to solve the localization issue for a WSN in which sensor nodes will be deployed as a grid topology and each sensor node has a RF communication device. We assume that one grid point has at most only one sensor node. Therefore, the set *DI* should contain the information of *GDU*, *GS*, the shadowing effect and the path-loss exponent. The shadowing effect and the path-loss exponent of a RF device are modeled in the Gaussian radio model.

3.3 *PK*

The pre-knowledge is defined as the knowledge that can be derived from the deployment information. For example, we can derive the probability of the connectivity between two sensor nodes when the distance of the two sensor nodes is given. From the connectivity probability, we can derive the probability of a sensor node that has n neighbors, where $n \geq 0$.

In the location model, five kinds of pre-knowledge are used. We have $PK = \{P(Conn(N_a,N_b)), P(Loc(N_a)), P(Deg(N_a)|Loc(N_a)), P(NNDL(N_a,N_b,Deg(N_b),Loc(N_b))|Loc(N_a)), P(KL(N_a,N_b,Loc(N_c),P_c)|Loc(N_a))\}$, where $P(Conn(N_a,N_b))$ is the probability of connectivity of two sensor nodes N_a and N_b under the Gaussian radio model, $P(Loc(N_a))$ is the probability of a sensor node on a grid point, $P(Deg(N_a)|Loc(N_a))$ is the probability of sensor node N_a that has $Deg(N_a)$ neighbors given location $Loc(N_a)$, $P(NNDL(N_a, N_b, Deg(N_b), Loc(N_b)) \mid Loc(N_a))$ is the probability that sensor node N_a whose neighbor N_b has $Deg(N_b)$ neighbors given location $Loc(N_a)$, and $P(KL(N_a, N_b, Loc(N_c), P_c) \mid Loc(N_a))$ is the probability that sensor node N_a knows P_c and the location of sensor node N_c via sensor node N_b given location $Loc(N_a)$.

3.4 *E* and *BR*

The relations of the location of a sensor node based on *DI* and *PK* can be modeled as a Bayesian Network as shown in Figure 1. A Bayesian network is a form of probabilistic graphical model, including nodes and arcs. Nodes represent variables and arcs represent the dependence relations among the variables. In Figure 1, there are four nodes and three dependence relations. The *Loc* variable has three arcs to the *NNDL* variable, the *Deg* variable and the *KL* variable since under different location we will have different number of neighbors or receive different messages from neighbors. The values of *NNDL*, *Deg* and *KL* are evidences in our location model. We use $v(NNDL)$, $v(Deg)$, and $v(KL)$ to denote the values of *NNDL*, *Deg* and *KL*, respectively. We have $E = \{v(NNDL), v(Deg), v(KL)\}$. The *Loc* variable is a query variable, which we want to know the probability after observing some evidences such as a value of *NNDL*, *Deg* or *KL*.

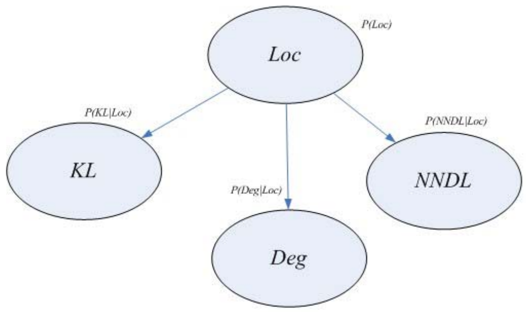

Figure 1. A Bayesian network depicts the relation about *Loc* variable.

When a sensor node observes new evidences, the sensor node can update the posterior probability of the location with new evidences by Bayes rule and then use this posterior probability as a new prior probability to calculate next posterior probability.

4. The CLPKBN Algorithm

In this section, we will introduce the CLPKBN algorithm based on the location model we proposed in Section 3. The CLPKBN algorithm consists of five steps. In the following, we explain each step in details.

The first step is to initialize *CandidateLocations*. *CandidateLocations* is a set of the possible locations of a sensor node, and contains the probability of each location. When a sensor node knows the number of its neighbors, it will update the posterior probabilities of the locations in *CandidateLocations* according to the location model we proposed.

In the second step, a sensor node receives a message and extracts evidences from the message. This step is to wait any *NNDL* or *KL* evidences. The evidence of the *Deg* variable is affirmative because the connections between all sensor nodes are stable. Thus, in the first step, a sensor node just computes the posterior probabilities of the locations in *CandidateLocations* once and uses the posterior probabilities as new prior probabilities when the sensor node knows the number of its neighbors.

In the third step, a sensor node will test whether the location of one sensor node is the same as the location of another sensor node. When the sensor node has high belief in their locations, which means that the *MaxBelief* of the sensor node is greater than *THRESHOLD*, the sensor node will check any contradiction between its location and the evidences. *THRESHOLD* value is set to 0.8. *MaxBelief* is the maximum probability of the locations in *CandidateLocations*. If a sensor node finds its location is the same as the location of another sensor node, it will compare its *TrustworthyValue* with the *TrustworthyValue* of another sensor node. If the *TrustworthyValue* of the sensor node is greater than the *TrustworthyValue* of another sensor node, it will discard this evidence and return to step 2 to wait new evidences. Otherwise, it will update the *CandidateLocations* according to the evidence. *TrustworthyValue* states that how confident of the location of a sensor node is.

In the fourth step, a sensor node updates the posterior probabilities of the locations in *CandidateLocations* according to the location model. Each sensor node knows *DI*. The *PK* can be calculated by each sensor node before the location estimation.

In the fifth step, if a sensor node finds the probability of some locations in *CandidateLocations* is greater than *THRESHOLD*, it will send a message with *id*, *MaxBelief*, *MaxBeliefLoc*, *kls* and *TrustworthyValue* to its neighbors. *MaxBeliefLoc* is the location with the maximal probability in the *CandidateLocations*. *kls* is a set of values of the *KL* evidences. *TrustworthyValue* is calculated as follow:

$$Trustworth\ yValue = \sum_{i \neq j} \frac{Dist\,(N_i, N_j)}{2}, \qquad (1)$$

where N_i and N_j are the sensor nodes of *NNDL* evidence. In Equation (1), a sensor node sums up the distance between the locations of sensor nodes of *NNDL* evidences. The evidences can help a sensor node to compute its location since more *NNDL* evidences means that the location has more evidences to support its location. The action of sending message can help sensor nodes to do the location estimation and to verify whether there exists any contradiction.

At the beginning of the execution of the CLPKBN scheme, the anchor nodes will send messages containing their *id*, *MaxBeliefLoc*(known by some manner), *MaxBelief*(1.0), and *TrustworthyValue* to their neighbors. Then the sensor nodes that receive the message start to process the messages. When some sensor node knows its location with high probability, which is greater than *THRESHOLD* in the CLPKBN algorithm, the sensor node will send a message containing its *id*, *MaxBeliefLoc*, *MaxBelief*, *TrustworthyValue*, *kls* to its neighbors. Repeat this process, more and more sensor nodes will locate its location afterward.

5. Performance Evaluations

To evaluate the proposed scheme, we implement the CLPKBN scheme and the Probability Grid scheme [17] on a simulator JProwler [21]. We use the Gaussian radio model to simulate radio propagation [6]. We have anchor nodes and sensor nodes deployed in gird topology. The hardware of an anchor node is the same as that of a sensor node except that an anchor node knows its location initially.

Several parameters, including grid size, transmission signal power, anchor percentage, shadowing effect, and deployment methods of anchor nodes are used as measurement metrics. The settings of these parameters are as follows:

- *Grid Size* (*GSize*): The grid size is set to {5x5, 10x10, 15x15}.
- *Transmission Signal Power* (*TSP*): The *TSP* is set to {80, 90, 100, 110, 120}.
- *Anchor Percentage* (*AP*): The *AP* is the number of anchor nodes divides by the total number of sensor nodes and anchor nodes. The *AP* is set to {0.05, 0.075, 0.1}.
- *Shadowing Effect* (*SE*): The *SE* is set to {0.0, 0.15, 0.3}.
- *Deployment for Anchor Nodes* (*DAN*): The *DAN* is set to {random, border}.

In the simulation, we evaluate the performance of the CLPKBN scheme and the PG scheme according to the combinations of the settings of parameters. For each combination, we randomly generate 700 wireless sensor network topologies as test cases. In the following, we give the comparisons of the CLPKBN scheme and the PG scheme to the simulation results.

5.1 Localization Errors under Various *GSize* and *DAN*

In this experiment, we evaluate the effect of various *GSize* and *DAN* on localization errors. *GSize* is set to {5x5, 10x10, 15x15} and *DAN* is set to {random, border}. *AP* is set to 0.1. The number of anchor nodes placed on a sensing area with 5x5, 10x10 and 15x15 grid point is 3, 10 and 23, respectively.

The simulation results are shown in Figure 2. From Figure 2(a), we can observe that the localization errors of the CLPKBN scheme are less than those of the PG scheme for all tested grid points. From Figure 2(b), we have similar observations as those of Figure 2(a). Compare the simulation results shown in Figure 2(a) and Figure 2(b), we can observe that the performance of both schemes under *DAN* = random is superior that under *DAN* = border for most tested grid points.

The only exception is the case where *GSize* = 5x5, the localization error of the CLPKBN scheme under *DAN* = random is higher than that of the CLPKBN scheme under *DAN* = border. The reason is that the CLPKBN scheme is a cooperative scheme. For the case *GSize* = 5x5 and the number of anchor nodes is 3, anchor nodes may not be able to cooperate to each other due to the random deployment scheme. However, when these 3 anchor nodes are placed at border of the terrain, they can cooperate to each other and result in a better result.

For the *DAN*= random case, the larger of the number of anchor nodes, the smaller of the localization errors of both the CLPKBN scheme and the *PG* scheme. For the *DAN*=border case, the larger of the number of anchor nodes, the larger of the localization errors of both the CLPKBN scheme and the *PG* scheme.

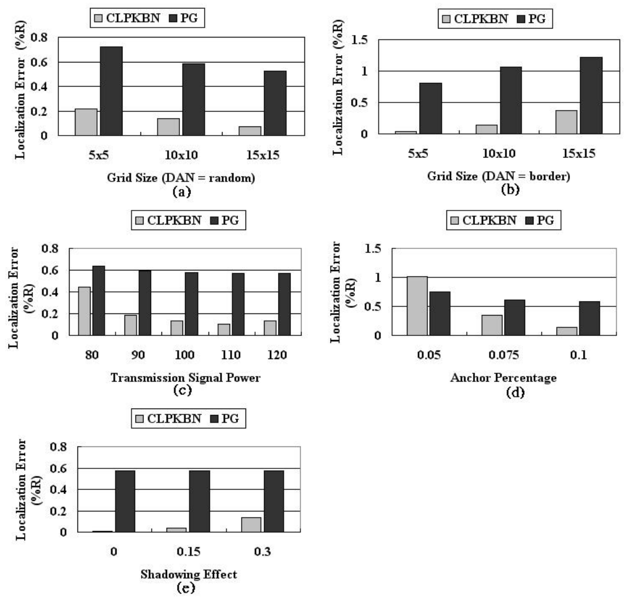

Figure 2. Localization errors under various (a) *DSize* (b) *DAN* (c) *TSP* (e) *AP* (e) *SE*.

5.2 Localization Errors under Various *TSP*

Since the setting of *DAN* = random results in a better performance than that of *DAN* = border, in the following discussions, all simulation results are based on the case where *DAN* = random.

The localization errors of the CLPKBN scheme and the *PG* scheme under different *TSP* are shown in Figure 2(c). From Figure 2(c), we can observe that the localization errors of the CLPKBN scheme are less that those of the *PG* scheme under for all tested *TSP* settings.

5.3 Localization Errors under Various *AP*

The localization errors of the CLPKBN scheme and the *PG* scheme under various *AP* are shown in Figure 2(d). The larger the value of *AP*, the more the number of anchor nodes. For the *DAN*= random case, the larger of the number of anchor nodes, the smaller of the localization errors of both the CLPKBN scheme and the *PG* scheme.

In Figure 2(d), for the *AP* = 0.05 case, the localization error of the CLPKBN scheme is higher than that of the *PG* scheme. The reason is that the number of anchor nodes in this case is small. Some anchor nodes may not be able to cooperate to each other due to the random deployment of anchor nodes. For *AP* = {0.75, 0.1} cases, the localization errors of the CLPKBN scheme are less than those of the *PG* scheme.

5.4 Localization Errors under various *SE*

The localization errors of the CLPKBN scheme and the *PG* scheme under various *SE* are shown in Figure 2(e). In this experiment, if we set the shadowing effect to zero, the sensor nodes will build a perfect regular network topology. When the shadowing effect increases, the number of neighbors of a sensor node is getting unpredictable, that is, the wireless sensor network topology is getting unpredictable. From Figure 2(e), we can observe that the localization errors of the CLPKB scheme are less that those of the PG scheme under for all tested *SE* settings. The localization error of the CLPKB scheme is sensitive to the value of *SE* while the PG scheme is not sensitive to the value of *SE*.

6. Conclusions and Future Work

In this paper, we have proposed a range-free localization scheme, cooperative localization with pre-knowledge using Bayesian Network (CLPKBN), to achieve high accuracy of locations of sensor nodes without hop-count information and high density of anchor nodes for a WSN. To evaluate the proposed scheme, we have implemented the CLPKBN scheme and the Probability Grid scheme on a simulator. From the experimental results obtained from the simulator, the CLPKBN scheme outperforms the Probability Grid scheme in most of test cases.

In the future, we will extend the location model to run at approximate deployment topology, that is, the possible locations for the sensor nodes are not countable since the distribution of *Loc* variable becomes a continuous distribution. The approximate deployment is more close to real deployment. For this approximate deployment topology, we will use maximum likelihood estimation (MLE) to solve the problem.

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