A Node Localization Approach Using Particle Swarm Optimization in Wireless Sensor Networks§

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***Abstract*—In the most applications of wireless sensor networks (WSN), the position of sensor node is important for the environment sensing, search and rescue, and geographical routing and tracking, and so on. This paper has proposed an accurate and simply scheme of mobile-assisted localization for the wireless channel loss model unknown environment in WSN. One localization algorithm is implemented using the particle swarm optimization (PSO). For improved the localization effect, the path planning strategy based on a kind of grid scan is suggested. To comparative evaluation of the proposed localization algorithm, the results of the localization algorithm based on multilateration in the same conditions are also provided. It is obtained that localization effect of proposed scheme is significantly better than localization scheme based on the multilateration for wireless channel loss model unknown environment. Furthermore, the weight factor τ in the constructed fitness function is also discussed. Overall, the simulation results have shown that the localization performance of PSO based on the mobile beacon is dependent upon the fitness function, the path planning of mobile beacon node.**

Keywords—Localization*; *Particle swarm optimization*; *Wireless sensor network*; *Mobile beacon*; *Grid scan

I. INTRODUCTION

A WSN is used in many applications, such as precision agriculture, industrial process monitoring and control, machine health monitoring, etc. In most applications, the position of sensor node is very important, such as environment sensing, search and rescue, and geographical routing and tracking, the position of each node should be known [1]. These requirements motivate the development of efficient localization algorithms for WSN.

In recent years, there have been many studies about the node localization of WSN [2-4]. They almost adopt the same strategy that the nodes with unknown coordinates are utilized by one or more GPS-equipped nodes with known coordinates in order to estimate their positions. However, each has both advantages and disadvantages. The GPS can provide the highly accurate location information, but it may not be feasible for most randomly deployed WSN, due to reasons of GPS cost, the high energy consumption of GPS-equipped nodes and so on. Therefore, one node localization technique which cut the cost and provides more accurate positions need be further study.

A promising method to localize for WSN by one mobile beacon has currently attracted extensive interest in the literatures[5-16]. In fact, in many harsh environments, although the terrain, the area is known, but the priori information related to the wireless channel loss model parameters are lack. Thus, the distance between nodes is not obtained directly by received signal strength indication (RSSI) information (we refer to as: the wireless channel loss model unknown environment). But to the best of the author's knowledge, it seems that how to design the strategy of the node localization for WSN with the unknown environment by the mobile beacon has been seldom addressed, which motivates our research in this paper.

This paper has proposed an accurate and simply scheme of mobile-assisted localization for the wireless channel loss model unknown environment. In the proposed approach, one mobile beacon node moves through the sensing field based on grid scan and transmits the mobile messages. And then, the unknown nodes apply the statistical median to compute their coordinates based on the advertised positions of the mobile beacon nodes. In this paper, one localization algorithm is implemented using the particle swarm optimization for the unknown environment. For increasing localization effect, the path planning algorithm based on a kind of grid scan is considered. To comparative evaluation of a localization algorithm based PSO, the results of the localization algorithm based on multilateration in the same conditions are also provided in simulation experiments.

II. PARTICLE SWARM OPTIMIZATION LOCALIZATION ALGORITHM FOR THE UNKNOWN ENVIRONMENT

A. Localization Model Based on RSSI

The Friis transmission equation is as follows. Given two antennas, the ratio of power available at the input of the receiving antenna P_r to output power to the transmitting antenna P_t is given by

$$\frac{P_r}{P_t} = G_t G_r \left(\frac{\lambda}{4\pi r}\right)^2, \tag{1}$$

where G_t and G_r are the antenna gains of the transmitting and receiving antennas respectively, λ is the wavelength, and r is the distance between the antennas. If the equation is modified

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and the Friis transmission model for free-space path loss is as follows,

$$L_r = 10\lg\frac{G_t G_r \lambda^2}{(4\pi r)^2 L}, \quad (2)$$

where L_r is the transmitting loss for the free-space at distance r, L is the system loss factor. However, in the actual application environment, the use of lognormal distribution model is reasonable.

$$L_d = L_r + 10\gamma\lg(d/r) + X_\delta, \quad (3)$$

where r is the reference distance (generally r=1m); L_r is the transmitting loss for the free-space at distance r and is calculated by (2); γ is the path loss factor. X_δ is the shadowing factor. If L_d, L_r, γ and X_δ is given, then the distance d between nodes can be obtained by (3).

Therefore, the environment with the unknown wireless channel loss model is defined as follows: for the certain application environment, if the path loss factor γ and the shadowing factor X_δ in (3) are unknown, then this environment can be defined as the environment with unknown wireless channel loss model. Thus, the node localization problem is converted to the nonlinear optimization problem in the environment with the unknown wireless channel loss model. Then the unknown node $i(x_i, y_i)$ is satisfy as follows,

$$\begin{cases} d = ((x_i - x_j)^2 + (y_i - y_j)^2)^{1/2} \\ L_{ijd} = L_r + 10\gamma\lg(d/r) + X_\delta, \end{cases} \quad (4)$$

where L_{ijd} is the observed value of wireless signal attenuation from the unknown node i to the beacon nodes j. (x_j, y_j) is the neighbors beacon nodes. L_r is the transmitting loss for the free-space at distance r. The unknown parameters $\phi_i = (x_i, y_i, \gamma)$ to be estimated should be satisfy $\Gamma_{ij}(\phi_i) = 10\gamma\lg(d/r)$, then, (3) can be expressed as $L_{ij} = \Gamma_{ij}(\phi_i) + X_\delta$. Thus, ε_{ij} is defined as the deviation of observed value L_{ij} from the estimate value $\Gamma_{ij}(\phi)$ and $\varepsilon_{ij} = |L_{ij} - \Gamma_{ij}(\phi_i)|$. Then, the total deviation is

$$\varepsilon(\phi_i) = \sum_{j=1}^{n} |L_{ij} - \Gamma_{ij}(\phi_i)|, \quad (5)$$

where n is the neighbors beacon nodes number of the unknown node i. Thus, for the environment with unknown wireless channel loss model, the localization problem based on RSSI is as an optimal problem for the objective function (6).

$$f(\phi) = \min \varepsilon(\phi_i) = \min \sum_{j=1}^{n} |L_{ij} - \Gamma_{ij}(\phi_i)|. \quad (6)$$

B. Localization Algorithm using Particle Swarm Optimization

PSO technique employs a population of candidate solutions that are moving these particles around systematically in the search space with random initial locations. Each particle is moved towards a randomly its location associated with the best solution (fitness) that the particle has come across so far in the search-space (called *pbest*) and the best position values encountered by the all particle population (called *gbest*) [17]. During the search process, each particle will update its velocity and position according to the following two equations,

$$\begin{aligned} V_{i,j+1} &= \omega V_{i,j} + c_1 r_1 (pbest_i - X_{i,j}) + c_2 r_2 (gbest_j - X_{i,j}) \\ X_{i,j+1} &= V_{i,j} + X_{i,j}. \end{aligned} \quad (7)$$

Therefore, the nonlinear optimization problem (6) is solved by PSO, here, the particle swarm solution space is $X_i^j = (x_i, y_i, \gamma)$, representing the x and y coordinates of the sensor node and the path loss factor.

Generally, WSNs are deployed with a limited number of beacon nodes. Hence, for improving localization accuracy, the iterative algorithm is used in this paper. The total deviation in iterative multilateration algorithm is defined as follows,

$$\xi(\phi_i) = \sum_{l=1}^{m} |L_{il} - \Gamma_{il}(\phi_i)|, \quad (8)$$

where m is the number of the ordinary beacon in participating localization and l is the beacon nodes. Then, based on (6) and (8), the fitness function is constructed as follows,

$$\begin{aligned} & fitness(\phi_i(k)) \\ &= \min(\tau\varepsilon(\phi_i(k)) + (1-\tau)\xi(\phi_i(k))) \\ &= \min(\tau\sum_{j=1}^{n} |L_{ij} - \Gamma_{ij}(\phi_i(t))| + (1-\tau)\sum_{l=1}^{m} |L_{il} - \Gamma_{il}(\phi_i(t))|). \end{aligned} \quad (9)$$

where τ is the weight factor in the interval (0, 1), k is the number of iteration.

Assume that the unknown parameters $\phi_i = (x_i, y_i, \gamma)$ to be estimated is bounded, $x = [o, a]$, $y = [o, b]$ and $\gamma = [o, c]$. Therefore, the equation (9) is translated as follows,

$$\begin{cases} \qquad equation\,(9), \\ s.t.\; g_j(\phi_i(k)) \ge 0,\; j = (1, 2, \cdots, 6), \end{cases} \quad (10)$$

where $g_j(\phi_i(k)) = (\phi_{i,1}(k), a - \phi_{i,1}(k), \phi_{i,2}(k), b - \phi_{i,2}(k), \phi_{i,3}(k), c - \phi_{i,3}(k))$, $j = (1, 2, \cdots, 6)$. Thus, for the feasible region $S = \{\phi(k) | g(\phi(k)) \ge 0\}$, the penalty function $P(\phi(k))$ is constructed as follows,

$$P(\phi(k)) = \begin{cases} 0, \phi(k) \in S, \\ K,\; else. \end{cases} \quad (11)$$

where K is the large number of selected in advance, then an augmented objective function is constructed,

$$F(\phi_i(k)) = \min(\tau\varepsilon(\phi_i(k)) + (1-\tau)\xi(\phi_i(k))) + P(\phi(k)), \quad (12)$$

Although $P(\phi(k))$ is a simple, but because of $P(\phi(k))'s$ discontinuity, the solving unconstrained problem (12) is difficulty. Therefore, $P(\phi(k))$ is revised to a penalty function with the positive parameter M (called the penalty factor),

$$P(\phi(k)) = M(k) \cdot \sum_{j=1}^{6} (\min(0, g_j(\phi_i(k))))^2, \quad (13)$$

the fitness function is constructed as follows,

$$fitness(\phi_i(k)) = \min(\tau\varepsilon(\phi_i(k)) + (1-\tau)\xi(\phi_i(k)) + P(\phi(k))). \quad (14)$$

The flow chart of proposed algorithm is formulated in Fig 1.

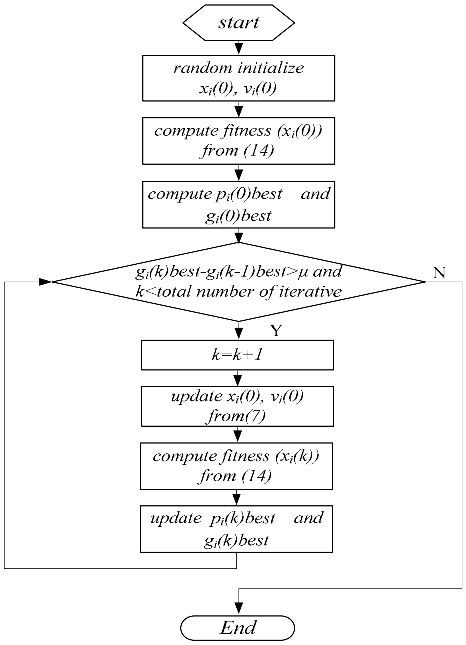

Fig. 1. Flow chart of proposed PSO algorithm

III. Path Planning Algorithm Based on the Grid Scan

A. Node Localization Algorithm

In this paper, the node localization algorithm includes the mobile beacon node broadcast algorithm and the unknown sensor node localization algorithm.

First, the mobile beacon node at first vertices of cell grid starts broadcast a Wake Up Signal (WUS) to wake up the unknown sensor nodes where are in the cell grid, and then broadcasts an Initial Start Signal, including the current vertex location information. Then the mobile beacon node will move the length of grid cell l to another vertices of this cell grid and when the mobile beacon node moves to this vertices, it will broadcast a Middle Stop Signal means the mobile beacon node has finished moving a cell grid side length. At the same time, the mobile beacon node constitutes to broadcasts an Initial Start Signal, and so on.

The other one is the localization algorithm of the unknown sensor node, which has the function of calculating the signal strength attenuation to obtain the distance through the broadcast receive from mobile beacon node. The unknown sensor nodes are in sleep state when they are waiting for the start signal until the WUS is received in the next action. Finally, an unknown sensor node calculates its node coordinate by three signal values using the PSO algorithm.

B. Moving Direction of the Mobile Beacon Node

When a mobile beacon node has been arrived the new vertices of cell grid, the next moving direction of mobile beacon need to determine. In this paper, we can use the moving direction scheme of mobile beacon node in [18]. The next movement direction of mobile beacon node is determined by the values of k_m. Therefore, there are the two cases, one is the even algorithm, other one is the odd algorithm.

IV. Simulation Experiments

In this section, we set 25 virtual beacon nodes and 25m communication radius in the sensor field. The scan line divides the square deployment area into 4 by 4 sub-squares and connects their vertexes using straight lines. And the 100 unknown nodes are deployed randomly in this sensor field. The moving direction of mobile beacon is shown in Fig. 2. The parameters are as follows: c_1=c_2=1.5, r_1 and r_2 is a random number uniformly in the interval (0, 1), the weight factor τ is 0.7, the population size N=40.

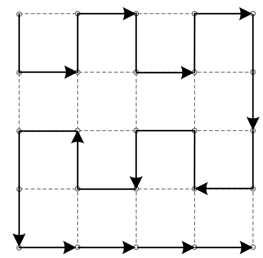

Fig. 2. Mobile path of beacon node in sensor field

Here, the results of the multilateration in the same sensor field are also provided and the path loss factor $\gamma = 1.5$ in (3). The shadowing factor δ is the main sources of interference. As shown in Fig. 3, the error in the two localization algorithms increases with increasing of δ. However, the localization algorithm based on multilateration has more sensitive to increasing of δ. Due to the multiple iterations to find the optimal solution, the noise from δ is weakened with the increasing of the average node connectivity.

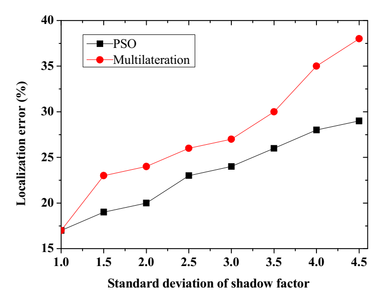

Fig. 3. Localization error and the standard deviation shadowing factor

Secondly, in condition of δ is ignored in (3), Fig. 4 shows that the relationship between the localization error and the connectivity. For multilateration algorithm, the virtual beacon node is used only in the course of node localization, so the localization accuracy is unrelated with the network connectivity. However, due to using the multiple iterations in the proposed method, the localization error gradually decreases with the increasing of the average node connectivity. When the average node connectivity is 15, the localization error of node reaches the minimum and maintains a constant.

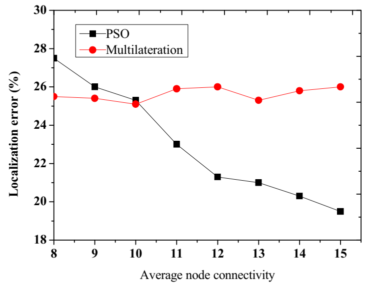

Fig. 4. Relationship between localization error and connectivity

Furthermore, we conduct a performance comparison of the fitness function (8)(Case 1) and (13) (Case 2) in PSO algorithm. As shown in Fig. 5, the localization error keeps constant in Case 1. However, in Case 2, the unknown node which has been completed the localization is as virtual beacon node in localization process of the current node. Thus, the localization error gradually decreases with the increasing of the average connectivity. Therefore, the higher localization accuracy is obtained by using the formula (13).

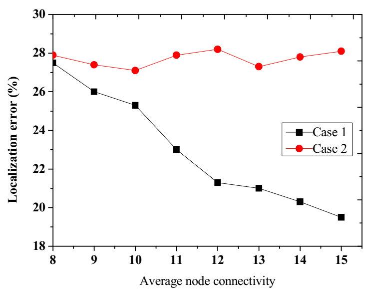

Fig. 5. Comparison of localization effect in different fitness functions

Finally, the τ is set as follows: 0, 0.5, 0.6, 0.7, 0.8. The simulation results are shown in Fig. 6.

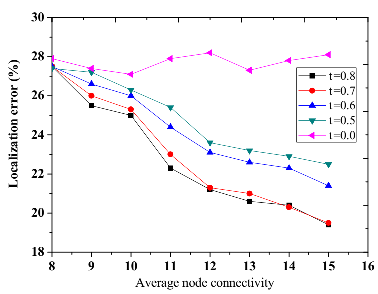

Fig. 6. Comparison of localization effect in different τ

When τ is 0, the localization error is high. When τ is 0.7, the average node connectivity arrives at 12.5%, the localization error decreases slowly and tends to constant. Furthermore, the localization effect is not significant when τ is increased to 0.8.

V. Conclusions

This paper has proposed an accurate and simply scheme of mobile-assisted localization for the wireless channel loss model unknown environment in WSNs. One localization algorithm is implemented using the particle swarm optimization for the unknown environment. For increasing localization effect, the path planning algorithm based on a kind of grid scan is considered. To comparative evaluation of a localization algorithm based PSO, the results of the localization algorithm based on multilateration in the same conditions is also provided. It is obtained that localization effect of proposed scheme is significantly better than the multilateration scheme for the wireless channel loss model unknown environment.

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