An improved node localization method for wireless sensor network based on evaluation of environment variables

Qingjian Ni, Cen Cao
School of Computer Science and Engineering, Southeast University
Nanjing, 211189, China
nqj@seu.edu.cn

ABSTRACT: *Node localization is an essential problem for some engineering applications in wireless sensor network (WSN). In this paper, an improved node localization method is proposed by combining the particle swarm optimization (PSO) and evaluation of environment variables. Firstly, the problem characteristics of node localization in WSN are analysed, and then a framework and a strategy for the settings of important parameters are given to solve such problems with PSO. Furthermore, the environment variable of WSN is evaluated and an improved node localization method based on PSO is proposed. In the proposed node localization method, the environment variable of WSN is evaluated during the process of ranging and the fitness function of PSO is designed according to the environment variable, and then the PSO algorithm is adopted to solve the node localization problem. Compared with the traditional methods, the results of simulation experiments show that the proposed method has good performance on the core indicators. Besides, for the proposed model and method, we also discussed the impact of several factors on the localization performance, which include the number of nodes, the number of failure nodes, the positioning error and the mean distance-measuring error.*

Keywords: Particle Swarm Optimization (PSO), Wireless Sensor Network (WSN), Node Localization, Environment Variable

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1. Introduction

Wireless sensor network (WSN) is a network consisting of a series of sensor nodes, which can transmit information through wireless signal and are capable of processing simple data. There are good prospects for WSN in many aspects, such as environmental monitoring, health treatment and military applications. Usually, several base stations on the ground are used as data processing center to help process data in WSN. Sensor nodes of WSN can collect information in the region to be monitored according to specific requirements. However, the performance of each sensor node is limited in computing capacity, energy and transmission bandwidth.

Node localization in WSN is a very critical issue, and it directly affects the efficiency of the entire network. According to different node localization methods, node localization in WSN can be divided into two categories: range based localization and non-range based localization. Range based localization locates nodes by measuring the distance between nodes, while non-range based localization locates nodes by network connectivity. In WSN, the nodes whose positions are known are called anchor nodes, and the others are called ordinary nodes. The location of an ordinary node can be determined by measuring the distance between the ordinary node and the anchor nodes.

The node localization problem in WSN can be described as an optimization problem [1-2]. Evolutionary computation is a method which can be applied to solving complex optimization problem [1]. Genetic algorithm (GA), evolutionary programming, ant colony optimization (ACO) algorithm and particle swarm optimization (PSO) algorithm are all evolutionary computation methods, where PSO algorithm is widely used to solve all kinds of complex optimization problems because it is easy to implement and has fast convergence rate. PSO algorithm has been introduced to solve the node localization problem in WSN [2-4]. However, most research used the basic PSO algorithm when selecting PSO variants. The setting of fitness function needs further discussion. This paper estimates the environment variables during distance measuring in WSN, and designs a reasonable fitness function with the environment variables. Furthermore, we propose a novel node localization method based on environment variables, and use PSO algorithm with dynamic inertia weight to solve the problem. Experiment results show that the proposed strategy has good positioning accuracy and high practicability.

2. Node localization problem in wireless sensor network

Node localization in WSN is a NP-hard problem [3]. Therefore, in practical engineering applications we can only find approximate optimal solution to this problem. The positioning error is an important measure of the algorithm performance.

In the node localization problem in this paper, ordinary nodes and anchor nodes are randomly deployed in a two-dimensional plane. The anchor nodes can determine the coordinates themselves, and the coordinates of the ordinary nodes need to be solved in this paper. These ordinary nodes are called target nodes.

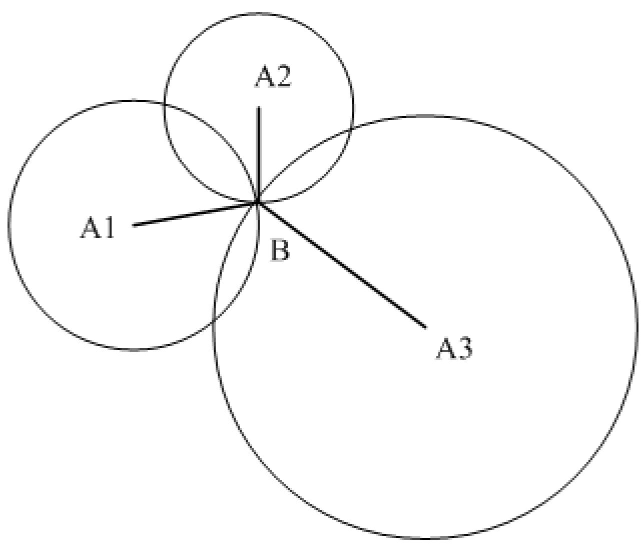

Figure 1. A schematic view of range-based localization

A simple localization method is based on distance measurement. Target nodes can determine their own coordinates by measuring the distance between target nodes and anchor nodes. As is shown in Figure 1, assuming node A1, A2, A3 are anchor nodes, node B is a target node. Each node has a signal transmission radius. If the radius of node A is R, and node B is in the circle whose center is A and radius is R, then node B can get the coordinates of node A. Node B can also get the distance between A and B. And assuming the distance is d, node B is in a circle whose center is A and radius is d. If node B can receive the signal from at least three anchor nodes, then theoretically the coordinates of node B can be calculated.

3. Particle swarm optimization fundamentals

PSO is one of the evolutionary computation methods, which is inspired by birds, fish and other group behavioral mechanisms. Since PSO is easy to implement and has relatively fast convergence rate, it is widely used in solving optimization problems in practical engineering applications. Taking PSO with inertia weight as an example, the basic process is as follows.

1) The individual particles are randomly distributed in the solution space;

2) For each particle, update the speed and position;

3) Update the best position of each particle and the optimal position of its neighborhood particles;

4) Repeat step 2) to 4) until the termination condition is satisfied.

The update equation of particle's velocity and position is shown in equation (1) and (2).

$$V_i(t) = \omega \times V_i(t\text{-}1) + \phi_1 \times rand_1(P_i\text{-}X_i(t\text{-}1)) + \phi_2 \times rand_2 \times (P_g\text{-}X_i(t\text{-}1)) \quad (1)$$

$$X_i(t) = V_i(t) + X_i(t\text{-}1) \quad (2)$$

Where ω is the inertia weight, which is used to indicate the influencing degree of the past speed of the current speed of the particle. The inertia weight value can affect search capability of PSO algorithm. When ω is large, PSO algorithm tends to explore the entire solution space, and is not easy to fall into local optimum, but not easy to converge. Conversely, when ω is small, it is easy to fall into local optimum but easy to converge. Therefore, in order to achieve a balance between search ability and convergence speed, we can use dynamic inertia weight. Initially, the weight is large, and as the iteration increase, the weight becomes smaller. As is proposed in [5], we can calculate the inertia weight according to equation (3).

$$\omega = (\omega_1 - \omega_2) \times \frac{MaxIter - CurIter}{MaxIter} + \omega_2 \quad (3)$$

Where ω_1 is 0.9, and ω_2 is 0.4. *MaxIter* is the maximum number of iterations, *CurIter* is the current number of iteration.

Neighborhood topology is another important setting of PSO algorithm [6]. In equation (1), P_i represents the position of the best particle in the neighborhood, and the neighborhood particle is defined by the neighborhood topology. The particles adjacent to a particle in the neighborhood topology are the neighbors of this particle. Commonly used neighborhood topologies are ring topology, fully connected topology and square topology. If the link between particles is relatively loose, the algorithm can find the optimal solution more easily but the convergence rate is slow. Contrarily, the algorithm converges fast but is easy to fall into local optimum.

Researches have shown speed limits can also improve the performance of the algorithm. On each dimension of the solution space, the particle's speed will have a maximum value, and the speed of particle cannot be greater than this value. If the speed of particle is greater than the maximum value, the speed will be changed to it. The maximum value of the k^{th} dimension of the particle's speed is calculated according to equation (4).

$$V_{max} = \frac{X_{max} - X_{min}}{N} \quad (4)$$

Where X_{max} is the maximum position particle reached in k^{th} dimension. X_{min} is the minimum position in k^{th} dimension. N is the value specified by user.

There are many excellent PSO variants, which have good performance in solving optimization problems in specific engineering field [7]. In this paper, PSO algorithm is used to solve node localization problems in wireless sensor networks.

4. Proposed node localization method based on PSO

4.1 Related Work

There are some initial results for the node localization problem using PSO. From the foregoing discussion, we can know it requires at least three adjacent anchor nodes to determine the position of the target node. When there are enough adjacent anchor nodes and long transmission radius of node signal, node localization method based on PSO algorithm can achieve good results.

In literature [8], all nodes are distributed in a plane, maximum likelihood estimation method is used to solve the node localization problem. The variance of the distance-measuring error is used as the fitness function of this problem, and then such localization problem could be considered as finding the minimum value of the fitness function. Literature [8] uses PSO algorithm to solve the problem, and compares the results with simulated annealing algorithm. Literature [9] uses Gauss-Newton iterative method and PSO algorithm for node localization problems. The experiment deploys nodes in a real environment and applies localization algorithm to microcontrollers, using pedometers to estimate distances. The experimental results show in certain circumstances PSO algorithm is better than Gauss-Newton iterative method on positioning accuracy. In literature [3], base stations are used to locate the nodes. There are four base stations surrounding the node. They form a quadrilateral and the coordinates of the four points of the quadrilateral are already known. By using RSSI technique, we can estimate the distance of the node to the four base stations. The distance can be represented by one-dimensional nonlinear function related to an environmental variable. Literature [10] also uses maximum likelihood estimation method, and changes the localization problem into finding the optimal value of a nonlinear function. All nodes are deployed by a small unmanned vehicle, which is equipped with a pedometer and a compass. So during the deployment process, the node can get the relative position of other nodes. During the localization process in literature [2], the nodes having been positioned are used as anchor nodes, to help locate the other nodes. During positioning, it takes into account the price of signal interaction.

The above studies generally do not focus on the model of node localization problems, and most of them use the basic PSO algorithm. This paper will introduce environment variables, and use PSO with dynamic inertia weight to solve the problem.

4.2 Node Localization Model Using Environment Variable Estimation

In this paper, all nodes in WSN are distributed in a plane area, the distance measurement of nodes will generate errors by the environment. By the central limit theorem, the error is a random number consistent with the Gaussian distribution. Assuming this error α is compliance with the Gaussian distribution, and the standard deviation is σ, which is determined by the actual environment.

$$\alpha \sim Gaussian(0, \sigma^2) \tag{5}$$

Let *d* represent the actual distance, and *d'* represent measuring distance. The positioning process is as follows.

1) Anchor nodes send their coordinate information to the other anchor nodes, and uses ranging technique to measure the distance between the anchor node itself and another anchor node nearby. Assuming the coordinates of anchor node A are (x_1, y_1), and the coordinates of anchor node B are (x_2, y_2), the measuring distance between nodes is *d'*. And then a sample of Gaussian distribution is obtained, as shown in equation (6) below.

$$g = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} - d' \tag{6}$$

All anchor nodes can obtain a sample of Gaussian distribution $g_1, g_2, g_3, \ldots, g_m$ by the above method, and then find the estimate value σ of the standard deviation α by equation (7).

$$\sigma' = \sqrt{\frac{\sum_{i=1}^{N} (g_i - E(g))^2}{N - 1}} \tag{7}$$

2) For an ordinary node, the coordinates are (x, y). Measure the distance between the node itself and the anchor node nearby. Assuming there are *m* anchor nodes near the ordinary node, the coordinates are (x_i, y_i), i=1, 2, 3, …, m, and then the measurement result is a collection $d_1', d_2', d_3',\ldots d_m'$. According to equation (8), we can obtain another sample of Gaussian distribution $h_1', h_2',$

h_3', h_m', and then use this sample to calculate the standard deviation by equation (7). The absolute value of the difference between the standard deviation ε calculated in this step and σ calculated in step 1) can be used as the fitness function of PSO algorithm.

$$h_i = \sqrt{(x - x_i)^2 + (y - y_i)^2} - d_i' \tag{8}$$

3) For every ordinary node, the method in step 2) is used until all the nodes have been processed.

$$f(x, y) = \frac{1}{m}\sum_{i=1}^{m}\left(\sqrt{(x - x_i)^2 + (y - y_i)^2} - d_i'\right)^2 \tag{9}$$

In addition, only using the above function as the fitness function of PSO algorithm may not obtain accurate node coordinates. In literature [8], equation (9) is used as the fitness function of PSO.

In this paper, weighted average of the function in literature [8] and the function in step 2) are used as the fitness function.

5. Experimental results and analysis

5.1 Experimental Settings

In this paper, *m* ordinary nodes are randomly deployed in a 20×20 plane, and *n* anchor nodes are also randomly deployed in the plane. These anchor nodes can determine their coordinates, while the ordinary nodes do not know their own position. The coordinates of ordinary nodes are the locations of the target nodes to solve in this paper.

In a 20×20 plane, coordinates are represented by (x, y). All the ordinary nodes and anchor nodes are randomly deployed in the plane, and we need to locate the ordinary nodes according to the method described in section 4. In the experiment, if the number of neighbors of a ordinary node is less than 3, then this node can not be located and will be regarded as a failure node. If the positioning result of an ordinary node is outside the 20×20 plane, this node is also a failure node. Node positioning error is defined as the Euclidean distance between the actual position and the result position. The mean positioning error of all the nodes which are not failed is used as the positioning error of the experiment. All the experiments were repeated 30 times, and the average is used as the final result.

5.2 Results And Analysis

The main parameters affecting the experiment results are the mean distance-measuring error σ, the number of anchor nodes and the maximum signal receiving distances between nodes. The number of anchor nodes and the maximum signal receiving distance between nodes will have impact on the number of neighbors of the ordinary nodes.

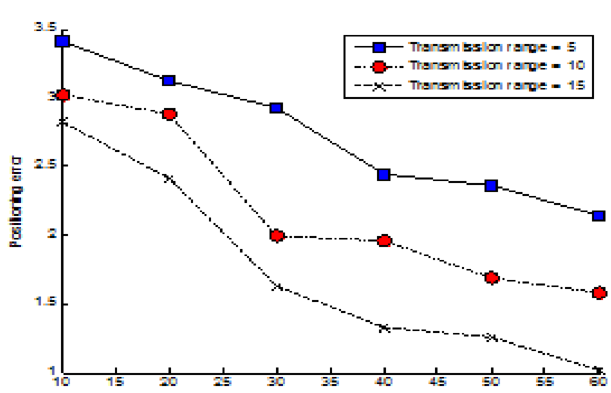

Figure 2. The relationship between the number of anchor nodes and the number of failure nodes when using the proposed method

Figure 2, Figure 3 and Figure 4 show the relationship among the number of anchor nodes, the number of failure nodes, the positioning error and the mean distance-measuring error when using the proposed method.

It can be seen in Figure 2 that when the transmission range is too small and the anchor nodes are few, most nodes failed in the localization. One reason is that there are no sufficient anchor nodes in the neighborhood to achieve the position of nodes. Another reason is that the positioning error is large, and the final position of the node is outside the region specified in the experiment.

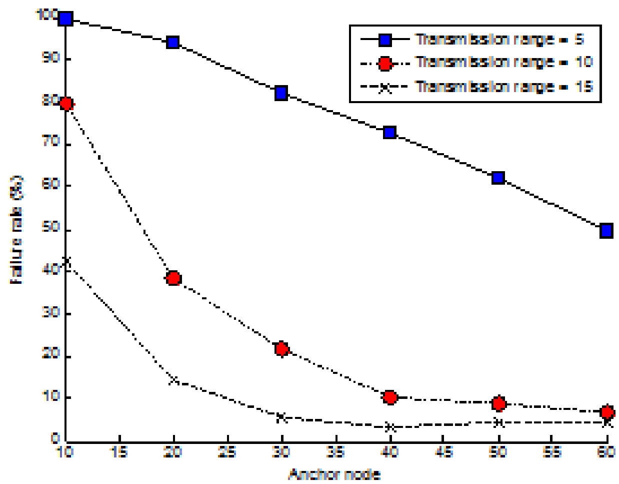

Figure 3. The relationship between the number of anchor nodes and the positioning error when using the proposed method

In Figure 3, the abscissa is the number of anchor nodes, and the ordinate is the positioning error. As can be seen from Figure 3, when the number of anchor nodes and the transmission range increase, the positioning error decreased significantly. This shows the node localization performance will be better when the number of anchor nodes in the neighborhood of the ordinary nodes decreases.

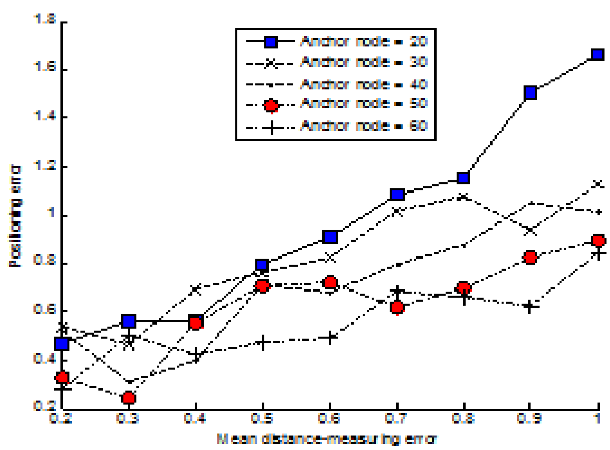

Figure 4. The relationship between the positioning error and the mean distance-measuring error when using the proposed method

From Figure 4, it can be seen that when the number of anchor nodes is small, the distance-measuring error has a greater impact on the final positioning result. When using more anchor nodes, the final positioning result was less affected by the distance-measuring error.

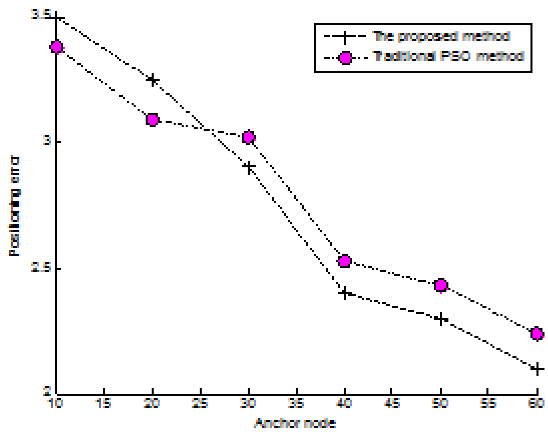

Figure 5. Comparison of positioning error between the proposed method and traditional PSO method with different anchor nodes

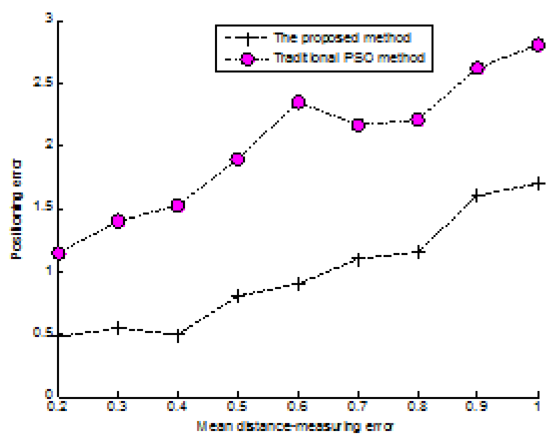

Figure 6. Comparison of positioning error between the proposed method and traditional PSO method with different mean distance-measuring errors

Figure 5 and Figure 6 show the comparison results between the proposed method and traditional PSO methods when transmission is 5. As is shown in Figure 5, when anchor nodes are few, traditional localization based on PSO algorithm has smaller positioning error. When the number of anchor node is larger, the proposed method in this paper has better performance. In Figure 6, in different mean distance-measuring errors, the proposed method in this paper has better performance than the traditional localization method.

Figure 7 shows the comparison results between the proposed method in this paper and the node localization method based on simulated annealing algorithm in [8] when the transmission range is 10. Under the same circumstances, the positioning error of the proposed method is smaller than the positioning error of simulated annealing algorithm.

According to the above analysis, it can be seen that the proposed node localization method for wireless sensor network based on evaluation of environment variables has higher positioning accuracy.

6. Conclusions

In this paper, according to the characteristics of node localization in WSN, environment variable is evaluated in the ranging process, and then fitness function is designed combining with environment variable and maximum likelihood estimate method,

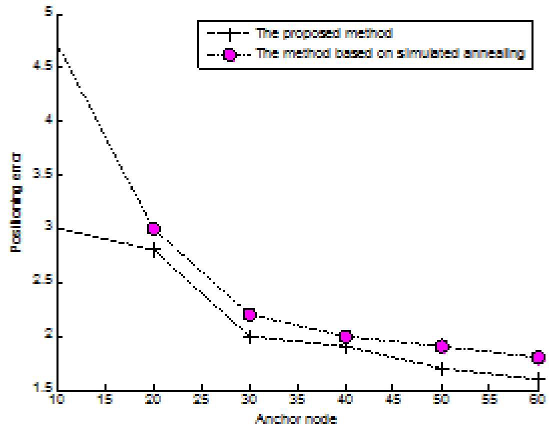

Figure 7. Comparison of positioning error between the proposed method and simulated annealing algorithm

ultimately, we proposed a new node localization strategy based on PSO. Specifically, in the simulation experiments, we used the PSO with variable inertia weight to solve the problem of node localization. Based on the experimental results, we analysed the relationship between the number of anchor nodes, the number of failure nodes, and the positioning error. We also compared the proposed method with the traditional method based on classical PSO and simulated annealing algorithm. Experimental results show that the proposed node localization method can get better positioning results.

In the future, we plan to further improve the proposed model for node localization problem. We also try to use a variety of newer PSO variants to solve such problems, compare and design better PSO variant suitable for solving such problems.

Acknowledgments

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