Monte Carlo Location Algorithm Based on Model Prediction

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***Abstract*—Location is the core of a wireless sensor network that provides basic information. Many existing algorithms focus on studying static networks while ignoring or not considering their mobility. The Monte Carlo localization (MCL) algorithm is the more prominent one in the dynamic network positioning algorithms. MCL positioning algorithm is in the context of self-organizing network, by the wireless sensor network technology, to locate the nodes in the dynamic network. This paper mainly introduces the Monte Carlo localization algorithm, and proposes an improved localization algorithm based on the Monte Carlo positioning algorithm combined with the establishment of motion model of the networks. The improved algorithm is based on the position of the node obtained by the Monte-Carlo Localization Boxed (MCB), and then the mobile node establishes a fast and effective prediction model to compare and screen, so that the relevant communication cost for the mobile nodes will be greatly reduced, and a series of problems brought about by mobility will also be simplified. The simulation results show that the improved algorithm can improve the positioning accuracy to a certain extent, and it is with more feasibility.**

Keywords—wireless sensor networks, Monte Carlo localization, mobile node, position prediction

I. Introduction

In the field of Wireless Sensor Networks (WSNs) [1], node location is a basic technology that can be used in some application to provide a lot of useful and basic information such as target tracking, environmental monitoring and protection, medical assistance, disaster prevention, etc. Most of the time and data recorded by the wireless sensors are meaningful only when they are in contact with the locations. So the positioning has been widely concerned by various industry applications.

The sensor node is the basic function unit of the wireless sensor network. Mobile ad-hoc networks [2] belong to a class of wireless communication networks that can form a fully mobile network without the need for infrastructure or with minimal infrastructure. Nodes have the function of data acquisition and data fusion forwarding. According to whether they need to measure the distance between the nodes, they are divided into range-based [3] localizations and range-free [4] localizations. The former needs to measure the absolute distance or orientation between the adjacent nodes, but it has high demand for hardware facilities. The latter does not need to measure the absolute distance or orientation of the nodes. According to the network connectivity, it is relatively simple to use the estimated distance between the nodes to calculate the node position with low cost, low power consumption, strong anti-noise ability and low equipment requirement. Monte Carlo location algorithm is a kind of range-free location algorithm used in dynamic networks.

The main indicators to evaluate positioning performance are positioning accuracy, anchor node density, the ratio of positioned nodes [5]. According to the existing research, most of the algorithms focus on ensuring the positioning accuracy while ignoring the energy consumption and other issues. In order to improve the utilization of the node while reducing the energy consumption of the node, it is very necessary to explore a safe and secure positioning algorithm This article proposes a Monte Carlo anchor box localization algorithm based on model prediction to achieve better performances in dynamic environment.

II. Related Works

Monte Carlo localization (MCL) algorithm was first proposed by Hu and Ivan for mobile sensor networks [6]. MCL algorithm focuses on two stages of prediction and filtering. By constantly judging and updating the collected sample points, it can make higher positioning accuracy. In [7], the authors proposed SMCL algorithm, based on the sequential Monte Carlo method, which is designed to estimate the position of the node by a random set of samples with associated weights. Forecasting, updating and resampling are the main steps of SMCLA. In [8], the authors proposed the MCL algorithm based on the reference node selection model. When the sample is selected by the reference node selection model, the adjacent nodes are selected into the reference node selection range, and the reference nodes which are close and distributed evenly are selected as possible to form the sampling box.

In [9], MCB algorithm based on the MCL algorithm is proposed by Baggio A. Not only in the filtering stage, but also in the prediction phase, if there is no information on the one-hop anchor node, the information of the two-hop anchor node can also be used alone. They created an area of overlapping anchor box for a hop anchor node and a two-hop anchor node within the broadcast range. In [10], the authors proposed IMCB algorithm based on the MCB algorithm. By analyzing the positioning results of the current time, the distance between the nodes and the relative position of the nodes, the sampling probability of the sample box of different regions may be obtained. The next sampling point may lag behind the posterior

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probability which effectively solves the problem of low precision caused by sample degradation in MCB algorithm.

In this article, we propose an improved algorithm which is based on the location of MCB algorithm and established the prediction model. By establishing a fast and effective prediction model compared with the location in MCB, it can screen out the nodes with little differences. Finally it can achieve the optimization of node location progress.

III. An Improved Algorithm Description Based on MCB Prediction Model

In the WSN node location process, the sampling area is too large, and the node constantly update the sample collection data, but they are less than the expected number of samples. The node received a useful anchor node information may be little, and it easily leads to greater error. This article proposes a series of screening judgments by selecting the Markov model through the secondary screening, and selects the nodes with high accuracy to assist the other location of nodes, then ensures the node location accuracy has a certain improvement.

A. The Establishment of Markov Model

When the research object is treated as a process, the stage can be divided into chronological or spatial characteristics, and this method can be used to establish the prediction model.

The state of the process at time t (k) is only related to the state at time t (k-1), independent of the previous state, and the stochastic process with this characteristic is the Markov process (Markov process) [11]. In order to speculate on the changing trends of things in the future, the basic idea of the Markov model is to find out the law of changes in the things in the past. State transitions are not deterministic but random, just as the movement of nodes. The Markov model is introduced for each time series to establish a Markov chain model describing the dynamic characteristics of the sequence. To get the dynamic Markov model, each eigenvector is used as the state of the model to analyze the order and order of each state transition [12]. The most important problem in the establishment of the Markov prediction model is to determine the transfer matrix. We use the regression analysis as a supporting tool based on a large number of observation data, find the transfer matrix of the Markov model, and establish the Markov model. We set up the random process: $\{X(t),\ t \in T\}$, and it's state space is I, for arbitrary number n in the parameter set T:

$$\begin{aligned} & t_1 < t_2 < \ldots < t_n, n \geq 3, t_i \in T \\ & P\left\{X\left(t_n\right) \leq x_n | X\left(t_1\right) = x_1 \cdots \mathrm{X}\left(t_{n-1}\right) = x_{n-1}\right\} \\ & = \mathrm{P}\{\mathrm{X}\left(t_n\right) \leq x_n \mid \mathrm{X}\left(t_{n-1}\right) = x_{n-1}\} \end{aligned} \tag{1}$$

It is said that the process $\{X(t),\ t \in T\}$ has a Markov nature, and calls this process the Markov process. The transition probability $P_{ij}(m, m+n) = P(X_{m+n} = a_j \mid X_m = a_i)$ is called the Markov chain at time $m + n$ in state m, the transition probability of the transition to the state a_i at time $m+n$. Transfer probability property is described as $\sum_{j=1}^{\infty} P_{ij}(m, m+n) = 1, j = 1, 2 \cdots$. The chain starts at any time a_i at time m, and must be transferred to one of a_1, $a_2 \cdots$ in another time $m+n$. Transfer probability matrix is as formula (2).

$$P(m, m+n) = \begin{pmatrix} P_{11}(m, m+n) & P_{12}(m, m+n) & P_{13}(m, m+n) & \cdots \\ P_{21}(m, m+n) & P_{22}(m, m+n) & P_{23}(m, m+n) & \cdots \\ P_{31}(m, m+n) & P_{32}(m, m+n) & P_{33}(m, m+n) & \cdots \\ \cdots & \cdots & \cdots & \cdots \end{pmatrix} \tag{2}$$

In order to find a pattern of node changes, we try to create a process model that can produce changes. We used the specific time step, state, and made the Markov hypothesis. With these assumptions, the system is a Markov process， and the Markov model is established. The observed states are: observed values, probability of initial state probability, probability of state transition, and the output of observation probability. We can calculate the likelihood that the predicted object is at a certain moment, like the next state position, and press the maximum likelihood as the selection result.

B. MCB Location Algorithm

This method is based on the MCL algorithm by creating a region called an anchor box. This box is an overlapping area of the one-hop anchor node and the two-hop anchor node within the broadcast range. Supposing n is the sum of the hop of the node to be determined and the information of the two jump anchor nodes, and (x_i, y_i) is the coordinates of node i, the position of the anchor box is determined by the maximum coordinate and the minimum coordinate as formula (3).

$$\begin{aligned} & x_{\min} = \max_{i=1}^{n}(x_i - r) \qquad x_{\max} = \min_{i=1}^{n}(x_i + r) \\ & y_{\min} = \max_{i=1}^{n}(y_i - r) \qquad y_{\max} = \min_{i=1}^{n}(y_i + r) \end{aligned} \tag{3}$$

For each hop received, the node establishes a square with a size of $2r$ centered on the anchor node position, and r is the propagation range. The establishment of the anchor box includes the calculation of coordinates $(x_{\min,} y_{\min,})$ and $(x_{\max,} y_{\max,})$, where the minimum value of x or the minimum value of y is greater than its corresponding maximum x region, and the box is reset to a box with only one hop anchor, or reset to the entire deployment area. Once the anchor box is built, the node only needs to collect the sample in the area it covers. Since the anchor box is the approximate propagation range of the anchor nodes, we maintain the filtering steps in the traditional MCL. The forecasting and filtering steps are repeated until the sample set is reached or until the maximum number of attempts has been reached. Fig. 1 shows an example of an anchor box created by three jump anchor nodes (the shadow portion is an anchor box).

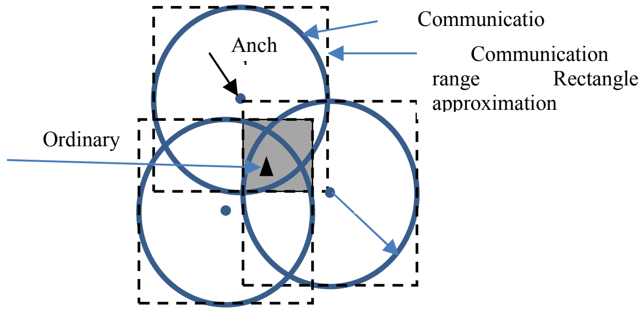

Fig. 1 An example of an anchor box

In the MCB algorithm, when the sample set is empty, such as at the initial moment, we can collect samples from the anchor box. However, when the sample was collected at the previous time, the new sample set needed to be collected from an additional restricted area is called the sample box. Thus, for each of the old samples L_{t-1}^{j} belonging to the set L_{t-1}, we create a square with a size of $2v_{\max}$ centered on the old sample. The sampling box is defined by formula (4):

$$\begin{aligned} x_{\min}^{j} &= \max(x_{\min} x_{t-1}^{j} - v_{\max}) & x_{\max}^{j} &= \min(x_{\max} x_{t-1}^{j} + v_{\max}) \\ y_{\min}^{j} &= \max(y_{\min} x_{t-1}^{j} - v_{\max}) & y_{\min}^{j} &= \min(y_{\max} x_{t-1}^{j} + v_{\max}) \end{aligned} \quad (4)$$

Once the sample box has been built, a new sample will be extracted from the overlapping area of the sample box and the anchor box for each old sample. This process improves the sampling speed, thus avoiding energy waste, and the response time of the method is less than the MCL method. After such a process, the sampling area is limited to a sampling box, which improves the sampling success rate, saves the computation amount, saves the positioning time and improves the positioning accuracy, and the performance has improved with the MCL algorithm.

C. Improved Location Algorithm

We use the MCB localization algorithm in [10] and improve it. However, this algorithm still has a large sampling range, the number of samples collected can't meet the desired number, and it is prone to large error for the location of the node. Based on the MCB algorithm, we establish the Markov model, propose an improved algorithm, and establish an effective prediction model. The range of problems caused by mobility will also be simplified, two times to limit the selection of the sample point, screen out the location which does not meet the conditions, and finally pick out the node with higher positioning accuracy. The flow chart of the improved algorithm is shown as Fig. 2.

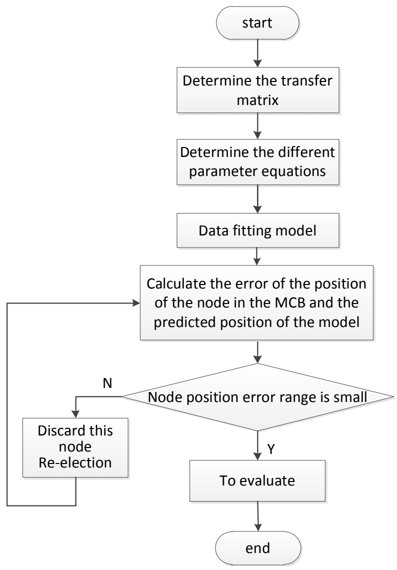

Fig. 2 Improved algorithm flow chart

Through the MCB algorithm, we can calculate the node at a certain moment of location information. At the same time, the position information of the node is processed, the transfer matrix is calculated, the data is processed, the Markov transfer matrix is determined by the least squares method, and then the measured value is compared with the predictive value. By the Markov's transfer matrix, the known data, the equation is determined, the data fitting is performed, and then the Markov model is determined. Then the position of the node predicted by the model is compared with the position of the node calculated by the MCB positioning algorithm to calculate the error between these two. If the error is small, then perform the test evaluation; if the error is large, then discard the node, and re-select the node with smaller position error, until the selection meets the required number of nodes. According to the maximum probability of the point, we can calculate the node in the t_n time for *x, y* direction of the value, at the same time, we can predict the node at this time in the *x, y* direction of the speed, as shown in formula (5).

$$\begin{aligned} v_x &= \frac{dx(t)}{dt}\bigg|_{t=t_{n-1}} \\ v_y &= \frac{dy(t)}{dt}\bigg|_{t=t_{n-1}} \end{aligned} \quad (5)$$

The velocity of the node is shown as formula (6)

$$v = \sqrt{v_x^2 + v_y^2} \quad (6)$$

The direction of motion is as shown as formula (7).

$$\theta = \arctan \frac{v_y}{v_x} \quad (7)$$

The improved algorithm is based on the MCB model. The distribution of each point at each initial point of time is calculated, and a large number of trajectories are used as the fundamental point of prediction, and the Markov model is established.

IV. Simulation Analysis

We perform the experiments in the simulation platform of MATLB R2014a. The nodes are deployed with unknown nodes and the anchor nodes. After the deployment, the nodes begin to move, respectively, by MCL, MCB positioning algorithm and the improved algorithm. The function model is established and the position estimation is carried out by the correlation algorithm. The Markov chain Monte Carlo method is used to estimate the mean of the likelihood function as the estimation of the locating coordinates. For the Monte Carlo calculation, the statistical average of the sample points is taken as the estimation result when the steady state is reached.

A. Movement of node

In the previous work, we could calculate the position of unknown nodes by MCL algorithm and the position of anchor nodes which has been set before. After that, we get a proportion of anchor nodes with low positioning error, which will be used to arrange the number of anchor nodes in WSN. The RWP (Random Way Point) model which is a moving node simulation model is used broadly in the study of traditional mobile ad hoc network. These nodes are arranged randomly and move as RWP model. After the movement, we could locate these nodes. The figure of arranged nodes and the distribution of moved nodes are shown as Fig.3.

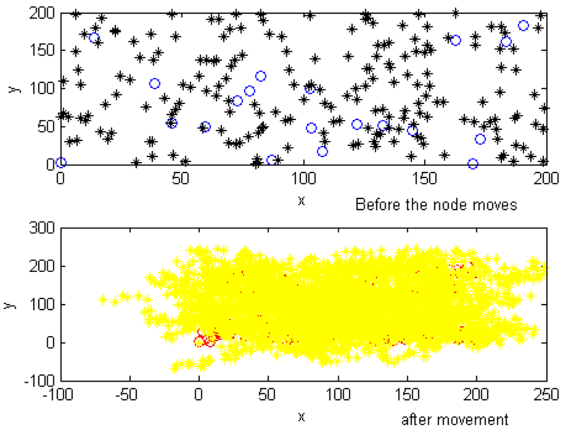

Fig. 3 The figure of distributed nodes in different stages

As the time going, the time of arranging will extend and the number of nodes will go up too. The accumulated error of unknown nodes will be resonated with an increasing tendency as a whole. The relationship between time and unknown nodes for the accumulated error is shown as Fig. 4.

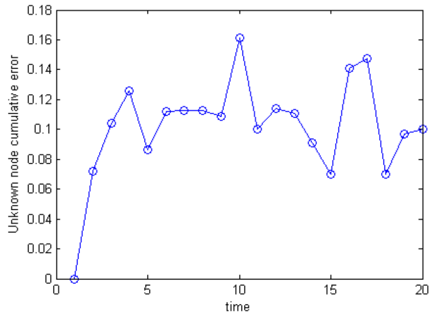

Fig. 4 The relation between time and unknown nodes accumulated error

B. The relationship between time and positioning error

We analyze the relationship between time and positioning error. Time and positioning error diagram is shown in Fig. 5. With the algorithm execution time lasting, the node positioning error is reduced, and the final stage of positioning error tends to be stable. With time increasing, the unknown node position is gradually calculated, and the error decreases and tends to be stable. Compared with the MCL algorithm, the MCB defines the sampling area through the anchor box. The improved algorithm predicts the position through the MCB model. As the execution time of the algorithm goes on, the historical position information is fully utilized, the node motion model is analyzed and the position prediction is carried out. The positioning accuracy of the improved algorithm is better than the other two algorithms.

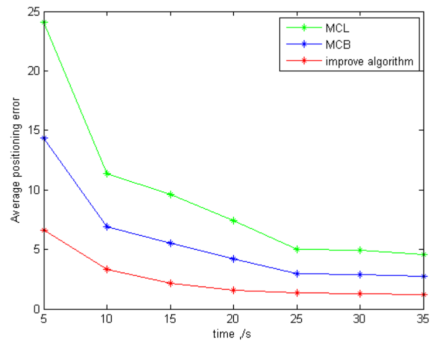

Fig. 5 Time and positioning error relationship diagram

C. Density and positioning error of anchor nodes

We know that there is a great correlation between the positioning error and the anchor node density in the location of WSNs, and the positioning error is affected by the anchor node to a certain extent, so the relationship between these two is always concerned. In order to further analyze the advantages of the proposed algorithm, we analyze the relationship between the average positioning error of the three positioning algorithms under the same conditions and the anchor nodes' density.

It can be clearly seen from Fig. 6 that the localization error of the three algorithms exhibits a decreasing trend with the increasing of the anchor nodes' density. With the increasing of the anchor nodes' density, the node with known position becomes more, the accuracy of the position of the unknown node could be calculated by the known nodes, and the node motion tends to be stable. In addition, the average positioning error of the improved algorithm in the three kinds of localization algorithms is the smallest, which further shows that the performance of the proposed algorithm has some advantages over the other two algorithms.

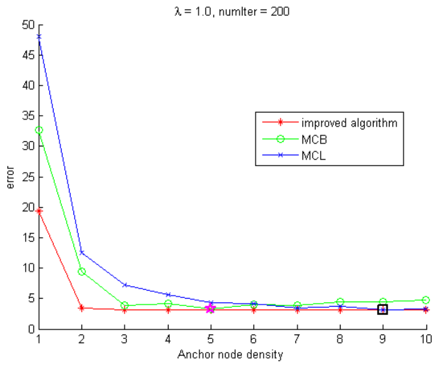

Fig. 6 Comparison of positioning errors

Therefore, the advantages of improved algorithms are shown. With the environment and other conditions permitted, the use of such improved algorithm is a good way to improve the positioning accuracy.

V. Summary

Up to now, WSN location problem has been widely studied and achieved some corresponding research results. But there are still some problems that have not been solved ideally. Location in the WSN is a core problem, and it always got more widespread attentions.

In this article, we introduce an improved algorithm based on MCB algorithm and with the combination of Markov model for node motion. Through the MCB, we can calculate node position. Compared with the established Markov prediction model, the second filter is performed. The average value is achieved accordingly, and the location of unknown node is got. It ensures the usefulness of the information from the anchor nodes, in the meantime, the processing time and energy consumption could be reduced. Due to the restrictions, it can avoid the information waste from the random sampling. The simulation results show that the Markov prediction model can well explore the law of node moving. By using MCB localization algorithm combined with Markov prediction model, the effective filtering of node location could be implemented and the node position optimization could be rationalized.

For the future work, we can focus on the detailed study of the balance of energy consumption and precision for node positioning. We can examine how the sample set size, acquisition quantity, and duration changes affect the positioning accuracy. We plan to do some new experiments in a variety of environments, and try to study the impact of using or not using some useless or negative information.

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