An Optimization Algorithm Based on the Monte Carlo Node Localization of Mobile Sensor Network

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Abstract — In classic Monte Carlo localization algorithm, Communication radius cannot be determined. In order to avoid the flaw, the paper presents an improved Monte Carlo localization algorithm based on transformation model between Hops and Hop Distance. The algorithm can estimate node's co-ordinates by obtaining hop information among nodes. Then a circular sampling area is produced. So the sampling efficiency is improved. The simulation results show that optimized algorithm can not only reduce times of positioning sample obviously, but also improve the accuracy of positioning effectively. In addition, whole network performance can also be improved when anchor nodes are a low-density. In classic Monte Carlo localization algorithm, variety of communication radius will impact effect of sampling directly. In the novel method, communication radius is replaced by hop. The flaw is solved thoroughly. Furthermore Positioning accuracy and sampling efficiency are upgraded as well.

Keywords-Wireless Sensor Network;Mobile Location;Monte Carlo;Hop Count/Distance Transformation Model;Sampling Optimization

I. INTRODUCTION

Wireless sensing technology has been widely applied in the information technology areas and the sensor node self-localization technology is fundamental to the wireless sensor network [1]. Only when most of the obtained data from the wireless sensor is combined with the location information will it possess the practical significance. Therefore, how to efficiently and accurately obtain the location information of each node is urgent for the research of wireless sensor network.

At present, most of the localization algorithms are designed for the static wireless sensor network. If the static sensor network localization algorithm is applied to the mobile sensor network, a series of problems will be caused, for instance, the accuracy of localization will be reduced because of the mobility of nodes, the node energy consumption is accelerated, etc. Some proposals are emerged in terms of the node localization of the mobile wireless sensor network. For instance, The University of Virginia proposed a dynamic triangulation algorithm; Massachusetts Institute of Technology presented a localization system based on AHLoS [2]. However, the proposals are not widely applied due to the high requirements for the anchor node density or the low location accuracy and other reasons. In the 10th International Conference on Wireless Communications, Networking and Mobile Computing (WiCOM), Lingxuan Hu et al. proposed the Monte Carlo dynamic node localization algorithm [3]. This algorithm breaks through the limitations of the application of the static sensor network localization algorithm into the dynamic sensor network, and makes full use of the sensor node mobility so as to achieve the good location accuracy. In the literature [4], this paper establishes the RSSI (received signal strength indicator) model to limit the sampling area and improve the efficiency of sampling. In the model, it solves the problems of maintaining the consistent communication range. However, the sensor hardware requirements are increased while the improvement of sampling efficiency is not significant. In the literature [5], the node motility and the sampling weights are combined based on the curve fitting so as to gain an area with the larger posteriori density value. In this way, it is able to optimize the sampling weights in the area. In the algorithm, the sampling number of wireless sensor is reduced. The sensor is required to retain the locations for at least three previous moments while the inconsistency of the node communication range is not solved. In the literature [6], the author puts forward the TSBMCL algorithm according to the MCB algorithm. On account of the insufficient anchor nodes near the unknown nodes, the ordinary nodes with the good locations are screened as the assistant position of the temporary anchor nodes. In the algorithm, it is able to satisfy the location requirement of mobile WSN with the low cost and high accuracy. However, the tedious calculation amounts of MCL samples are not solved [7].

However, it is unable to determine the communication range of the sensor node in practice. The sampling procedure is complicated for the classic Monte Carlo localization algorithm while the sampling efficiency is low. This paper proposes a Monte Carlo localization algorithm in the combination of hop count/distance transformation model. In this algorithm, it can avoid the direct use of node communication range to determine the sampling area and there is no requirement on the additional ranging hardware. A better location performance is achieved.

II. MONTE CARLO LOCALIZATION ALGORITHMS

The Monte Carlo method is also known as the statistical simulation method, a kind of numerical computation method based on the theory of probability statistics. In 2004, someone firstly applied the concept of probability statistics into the node location areas of wireless sensor network. The Monte Carlo method is not constrained by the node mobility of mobile sensor network, and makes the good use of the node mobility to assist the node location [8].

In the application areas, the Monte Carlo method can be summarized into three main steps: construct or describe the probability process, conduct the sampling from the known probability distribution and establish all kinds of estimators. The application of Monte Carlo method into the mobile WSN node localization can be described as [9]:

(1) Combine the location l_{t-1} for the previous moment on each unknown node and the motion model of each unknown node, get a circular and uniform sampling area for each unknown node location at the present moment and conduct the sampling in the sampling area;

(2) Filter the samples in the combination of each unknown node and the observed range information of the neighboring anchor node. The filtering condition is:
$filter(l) = \forall s_1 \in S_1, d(l, s_1) \le r \cap \forall s_2 \in S_2, r < d(l, s_2) \le 2r$ In the equation, S_1 represents the single hop anchor node coordinate; S_2 represents the double hop anchor node coordinates; r represents the communication range of each node; l represents the sample coordinates;

(3) Filter out some samples, repeat the above steps until there are enough samples, and give the same weight to each sample location. According to the sample coordinates and the weights of each sample, it is able to estimate the unknown node location [9, 10].

In the ideal condition, the classic Monte Carlo localization algorithm will get the good positioning effect. In practice, it is unable to obtain the required and ideal parameter values based on some algorithms on account of the geographical location, weather, obstacles and other reasons, for instance, the sensor node communication range will be different with the change of the geographical position. Especially when the height of the node is changed, its communication range will go through a bigger transformation. In order to solve these problems, we need to make some improvements on the original algorithm to get a better application into practice.

III. AN OPTIMIZATION ALGORITHM BASED ON THE NEW MONTE CARLO LOCALIZATION

Based on the Monte Carlo method, the author puts forward a mobile sensor network node localization algorithm called HDMCL. In the algorithm, the hop counts between the sensor nodes are used to estimate the range information of the unknown node and anchor node and calculate the forecasted coordinate of the unknown node by reusing this range information. Through these coordinates, it can plan a refined sampling area and take the place of the classic Monte Carlo algorithm by constraining the sampling area based on the communication range. It can solve the big fluctuations of communication range and get a certain promotion on the location accuracy and sampling efficiency.

A. Node Information Dissemination Stage

In the initial stage of each location, each node will flood and spread the navigation aid information in the sensor network. The navigation aid information identifies ID and the hop count based an initial value 0. The anchor nodes need to flood the above information and their exact location information $\{x_i, y_i\}$. Each unknown sensor node keeps an anchor node table $\{ID_i, x_i, y_i, h_i\}$. In this period, the unknown node will collect the anchor node information and send the receiving information to the other unknown nodes. ID_i represents the identification number of anchor node; x_i and y_i represent the location of the anchor nodes; h_i represents the hop count.

B. Hop Count/Distance Transformation Model (H\D Transformation Model)

In the wireless sensor network, it needs to install the additional ranging hardware in obtaining the range information between the nodes. It is cumbersome with the high energy consumption. However, it can easily obtain the minimum hop counts between the nodes. Through the following three steps, H \ D transformation model can realize the conversion of the hop count and range between the nodes:

(1) In the network, all the nodes are flooding the hop count with the initial value 0. For each hop, the hop count is added by 1. Meanwhile, it will receive the hop count information from the adjacent nodes. Upon the exchange of hop count information between the nodes, all the network nodes can obtain the minimum hop count value with the

other nodes.

(2) Except for the flooding and the receipt of hop count information, anchor nodes are also required to spread their coordinate values. Based on these coordinates, the anchor node s_k will calculate the range with the other anchor nodes, and make the statistics on the sum values of s_k with the other anchor nodes and the hop count, which they are respectively marked as D_k and H_k. k represents the serial number of anchor nodes. The ratio of D_k and H_k (remarked as D_k/H_k) is the average hop range value of the anchor node that is recorded as d_k.

(3) The average hop range value obtained from the unknown node and an anchor node with its minimum hop count is seen as the average hop range value that is recorded as l_k. The unknown node will re-use the average hop range value to multiply by the hop counts with the other anchor nodes that are recorded as $l_k * j$, namely obtain the range information of the node with all the anchor nodes.

C. Etermine the Circular Sampling Areas

In this paper, the hop count information is combined with H/D transformation model, predicting the estimated coordinate of the unknown node at each independent localization time period and re-using the estimated coordinates to draw a circular sampling area and improving the Monte Carlo localization algorithm.

After the information transmission of the node, each node can obtain the hop counts with the other nodes. h_{ij} expresses the counts between the node i and node j; n represents the total node number; i and j represent the node identification number. According to the hop count and H\D transformation model $h_{ij}, i \in [1,n], j \in [1,n]$, it can easily calculate the range of each unknown node with the other anchor nodes that will be recorded as $d_{\alpha\beta}$. α is the identification number of the unknown node in the network; β is the identification number of anchor node in the network.

After obtaining the above information, it is suggested the unknown node coordinate is (x_i, y_i); the anchor node coordinate is (x_1, y_1) $(x_2, y_2)\cdots(x_n, y_n)$; based on the multilateral measurements, it is able to calculate the estimated coordinates of each unknown node. Its specific flow is stated as follows:

(1) The unknown node coordinates and the Euclidean distance of each anchor node are respectively represented in the equation set.

$$\begin{cases} (x_1 - x_i)^2 + (y_1 - y_i)^2 = d_{i1}^2 \\ (x_2 - x_i)^2 + (y_2 - y_i)^2 = d_{i2}^2 \\ \quad\vdots \\ (x_n - x_i)^2 + (y_n - y_i)^2 = d_{in}^2 \end{cases} \tag{1}$$

(2) In the equation set(1), it needs to subtract the Equation 1 from Equation 2 to Equation n and get a new equation set.

$$\begin{cases} x_1^2 - x_n^2 - 2(x_1 - x_n)x_i + y_1^2 - y_n^2 - 2(y_1 - y_n)y_i = d_{i1}^2 - d_{in}^2 \\ x_2^2 - x_n^2 - 2(x_2 - x_n)x_i + y_2^2 - y_n^2 - 2(y_2 - y_n)y_i = d_{i2}^2 - d_{in}^2 \\ \quad\vdots \\ x_{n-1}^2 - x_n^2 - 2(x_{n-1} - x_n)x_i + y_{n-1}^2 - y_n^2 - 2(y_{n-1} - y_n)y_i = d_{i(n-1)}^2 - d_{in}^2 \end{cases} \tag{2}$$

A represents the coefficient of the equation set

$$A = \begin{bmatrix} 2(x_1 - x_n) & 2(y_1 - y_n) \\ \vdots & \vdots \\ 2(x_{n-1} - x_n) & 2(y_{n-1} - y_n) \end{bmatrix} \tag{3}$$

b represents the constant term of the equation set

$$b = \begin{bmatrix} x_1^2 - x_n^2 + y_1^2 - y_n^2 + d_n^2 - d_1^2 \\ x_{n-1}^2 - x_n^2 + y_{n-1}^2 - y_n^2 + d_n^2 - d_{n-1}^2 \end{bmatrix} \tag{4}$$

(3) Figure out the estimated coordinate value of the unknown node

$$\hat{X} = (A^T A)^{-1} A^T b \tag{5}$$

Through the above method, it is able to calculate the estimated coordinate value of each unknown node at each independent localization period. Meanwhile, at each separate localization time period, each unknown node will synchronously update its observation information, extract the single and double hop anchor nodes from the observation information at each unknown node so as to jointly construct a refined circular sampling localization area (Refer to Fig. 1):

The point O is the estimated coordinate of the unknown node based on the calculation of the hop counts between the nodes through combining H/D transformation model and multilateral measurement method. The points A, B and C respectively represent the observed coordinate information of single and double hop anchor node of unknown nodes at the current localization time periods, respectively calculate the Euclidean distance of the anchor nodes A, the anchor node B and the anchor node C with the estimated coordinate point O, which they are respectively recorded as r_A, r_B and r_C. These values are the reference ranges to construct the circular sampling area. Then it needs to take the anchor node A as the center of a circular as an example, refer to the radius r_A that is respectively multiplied by the parameter factors α and β. $r_A * \alpha$ and $r_A * \beta$ are respectively seen as the inner ring and outer ring radius in the circular area. The anchor node A is taken as the center and $r_A * \alpha$ and $r_A * \beta$ are the radius to draw the circular areas. In a similar way, it can draw the circular area based on the radius of the other another nodes and obtain the intersection of the circular area. The intersection part is the sampling location area as the shadow grid area in Fig.1.

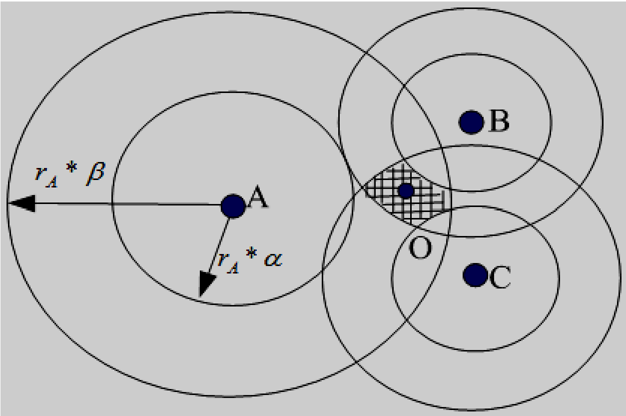

Fig.1Circular Sampling Area Construction

Choosing the appropriate parameter factor α and β is crucial to construct a circular sampling area. If the value is too big, it will lead to the reduced sampling efficiency; if the value is too small, the sampling area might not cover the real node coordinates. Considering the error estimate coordinates and the error is uniformly distributed within a certain range, the inner ring and outer ring of the circular areas are shrunk or expanded with the reference of the circle in a geometric proportion. In this way, the α and β values should be classified as $1-\varepsilon$ and $1+\varepsilon$. ε is the constant of the section $(0,1)$. Through a large number of simulation experiments, it is found when ε is 0.3, namely α=0.7 and β=1.3, the sampling area will cover the true coordinate position of the unknown node with the minimum cost.

D. Implementation of Optimization Algorithm

Suppose the rectangular region of location deployment is defined as $\{(x,y)\,|\,0 \le x \le x_{range}, 0 \le y \le y_{range}\}$. Whereas, O_t represents the observation information of the unknown node at the location time period; L_t is the sample location information set in the t time period; A_t is the sampling area in the t time period.

Initialization

construct the initial sensor network node deployment

$$x_0^i = x_{\min} + (x_{\max} - x_{\min}) * random(0,1) \text{ ,}$$

$$y_0^i = y_{\min} + (y_{\max} - y_{\min}) * random(0,1)$$

// make a random deployment of the nodes in a rectangular region

Forecast Period

In the network, all the nodes must follow the RWP (RandomWayPoint)model and forecast the node location at the next time period

For each sample in L_{t-1}

l_t=RWP (l_{t-1}) // After following the RWP model, it will get the node location at the next time period

Done

Filtering & Normalization Stage

While the sample size is less than N in l_t

For all the samples in l_t // filter the sample and keep the samples satisfying the filtering conditions

filter through the circular sampling area A_t // get a refined circular area

Done

Done

If sample size is equal to N in l_t

The final forecasting node location is the geometric center of all the sample locations

Done

IV.SIMULATION & ANALYSIS

The data results are analyzed through the MATLAB R2013B simulation software. The simulation environment is stated as follows:

TABLE I. SIMULATION PARAMETER SETTING

Simulation Region Size	500*500(m)
Sensor Node Number	160
Ration of Anchor Nodes	10%
Max. Running Speed of Sensor Node	20(m/s)
Node Communication Range	80(m)
Sample Size	100

All nodes are randomly distributed in the area, and follow the RWP motion model, namely the node movement is set in a random direction and the speed is randomly elected in the range $[0, v_{\max}]$; the node can perceive every node communication range and implement the data exchange and transmission. But there is no ranging capacity for the node so that the range cannot be measured with the surrounding nodes. In the wireless sensor network, it is unable to know the node distribution at the next moment based on the node distribution at the current moment. After the nodes reach up the location time period, it will interact with each other and continue to follow the random motion based on RWP model.

A. Location Accuracy

In Fig.2, two curves respectively describe the average localization errors for all the nodes in the wireless sensor network based on the MCL algorithm and HDMCL algorithm as time goes by. Location error refers to the ranging difference of the final estimated location and the actual location for the unknown node while the average localization error is the mean value of location error for all the nodes. The average location is analyzed on the simulation at the former ten time periods.

It is seen that the average localization error will not be increased or decreased as time goes by. It will be increased or decreased in an irregular way. This is because time is divided into N time periods for each location. After the location is finished in the previous time period, it will conduct the location at the next time period. The location is relatively independent at each time period. In the location process, the filtering conditions are refined. It is seen that in the wireless sensor network, the average localization errors of all the nodes based on the HDMCL algorithm are slightly reduced than those of the classical MCL algorithm. The optimization proportion is ranged from 3% to 8% and the location accuracy is increased by an average of 5.01%.

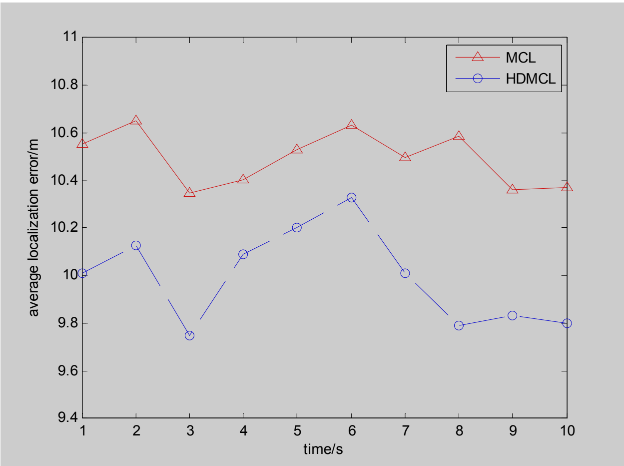

Fig.2 Comparison Chart of Location Accuracy Based on MCL Algorithm and HDMCL Algorithm

B. Sampling Efficiency

The Monte Carlo method is a solution based on the concept of probability statistics. In general, it needs to pass a lot of repetitions to obtain the final result. In this paper, the optimization purpose is to get the most accurate result under the precondition of the minimum test times. In the project, the author makes the comparative analysis on the sampling number. It is known that the average location accuracy and location efficiency based on HDMCL algorithm has the better optimization effects than that of the MCL algorithm.

In Fig.3, the sampling number based on HDMCL algorithm is reduced from 100 to 50 while the sampling number based on MCL algorithm is still 100. Fig.3 shows the comparison chart of node location error when the other location condition is not changed. It is seen that the node location accuracy is still raised by 3.57% in comparison of the traditional MCL algorithm. This is because in the HDMCL algorithm, the sampling area is composed of intersection areas of several circular areas. Compared to the classic MCL algorithm, it can cover a larger area with the sample posterior probability density so that each sample is closer to its actual coordinate position. Under the condition of fewer samples, the location effect is still significant in greatly improving the sampling efficiency.

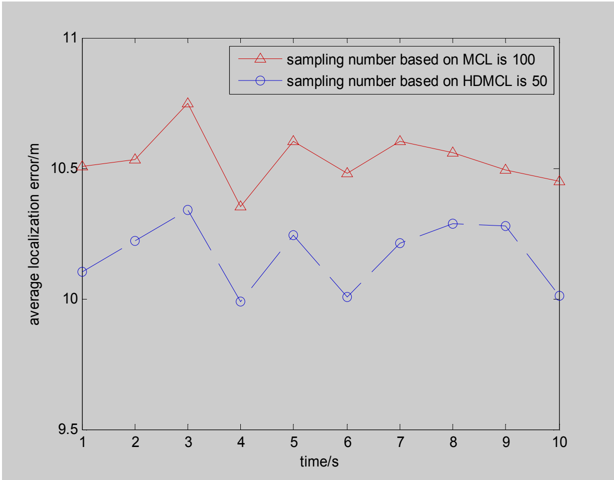

Fig.3 The Effects of Sampling number on the MCL and HDMCL Algorithms

C. Anchor Node Density

Anchor node density is an important reference index of the node localization in the wireless sensor network. Anchor nodes are possible to successfully measure its coordinate position, but the costs are high. If the network anchor node density is increased, the location accuracy will be ascending to a certain extent with a higher location cost. If the anchor node density is decreased, the location cost is reduced with lower location accuracy. In reality, it must weigh the benefits between the network cost and location accuracy requirements.

In the paper, the author makes an analysis on the unknown node location with the different anchor nodes in the network. The anchor nodes are ranged from 7 to 25, respectively and conduct 20 operations in each experiment independently and finally take a mean value for 20 operations as the average localization error value. In each experiment, the mean value of running results for 10 seconds is seen as the end value. In Fig.4, it is seen that the average localization error value is reduced with the increase of the anchor node density. When the anchor node density is lower, the optimization results of location accuracy based on the HDMCL algorithm were much significant compared to the classic MCL algorithm. In the filtering process based on HDMCL algorithm, it is easily found that this is because in the HDMCL algorithm, it firstly uses the hop count information to get the estimated coordinate position, and get a circular sampling area based on the estimated coordinates. In the process, it can realize the location when the unknown node can perceive the position information of three anchor nodes. With the low anchor node density, the location effect based on HDMCL algorithm is better compared to the MCL

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algorithm. That is to say the effect with the low anchor node density is more obvious compared to the high anchor node density.

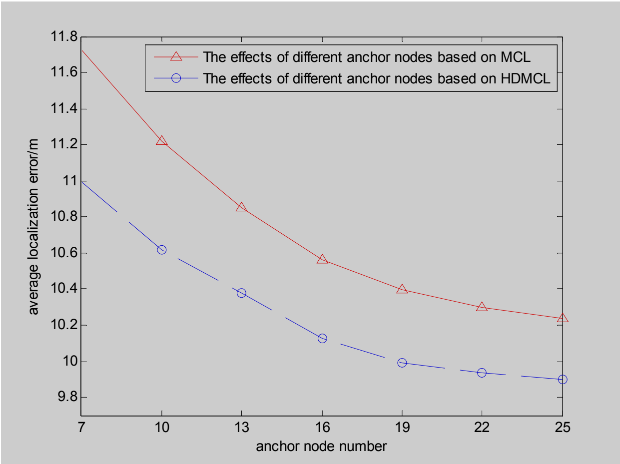

Fig.4 The Influence of Anchor Node Density on the Node Location

V.CONCLUSION

In terms of the mobile wireless sensor network, this paper proposes an optimization algorithm based on the Monte Carlo algorithm. The algorithm adopts the mutual perception of the node hop count information with the anchor nodes and obtains a refined circular area. The location effect is better. Simulation results show that the algorithm has a better location accuracy compared with the Monte Carlo method. In addition, there is a dramatic improvement in terms of sampling efficiency. When the anchor node density is lower, the optimization effect is more obvious in the wireless sensor network environment. In the algorithm, the calculated amount is added in the determination process of sampling areas. For the mobile network, it has a practical significance to sacrifice a certain internal space to ensure the location efficiency and accuracy. In addition, the location effect based on the current algorithm is better in the regular network environment, but it cannot be better applied into the complex terrain that is similar to U and C regions that the location effect is poor. At this point, it is still an open question.

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