An Efficient Localization Method for Mobile Nodes in Wireless Sensor Networks

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Abstract—With the development of electronic technology and communication protocols, wireless sensor network technology is developing rapidly. In a sense, the traditional static wireless sensor network has been unable to meet the needs of new applications. However, the introduction of mobile nodes extends the application of wireless sensor networks, despite the technical challenges. Because of its flexibility, the mobile wireless sensor network has attracted great attention, and even small, self-controlled mobile sensor devices have appeared. At present, mobile node localization has become one of the hotspots in wireless sensor networks. As the storage energy of wireless sensor network nodes is limited, and the communication radius is small, many scientists have focused their research direction on the location algorithm of mobile nodes. According to the continuity principle of mobile node movement, in this paper we propose an improved mobile node localization algorithm based on the Monte Carlo Location (MCL) algorithm, and the method can reduce the sampling interval effectively. First of all, this paper introduces the structure and classification of wireless sensor localization technology. Secondly, the principle of the Monte Carlo Location algorithm is described in detail. Thirdly, we propose an efficient method for mobile node localization based on the MCL algorithm. Finally, the effectiveness and accuracy of the new algorithm are verified by comparative analysis.

Keywords—Wireless sensor network; Mobile node; Location algorithm; Monte Carlo Location

1 Introduction

As a new type of network communication technology, Wireless Sensor Networks (WSNs) are widely used in many fields, such as environmental monitoring, military target tracking, the medical and health fields and intelligent traffic monitoring [1]. The WSN combines sensor technology, embedded technology, wireless communication technology, and so on. By monitoring the nodes in the monitoring area, the remote control center realizes the centralized processing of the monitoring data. With the development of science and technology, the function of the sensor is becoming more and more perfect. As the result of lower cost and higher performance, WSNs are being used in a growing number of fields [2]. At present, the static node localization algorithm for WSNs has become mature, and the theoretical research results are relatively rich. However, most of these algorithms do not consider the mobility of nodes, so they cannot solve the problems of mobile nodes' localization.

Designing a suitable WSN mobile node localization algorithm has become a hot research issue. Many scientists are trying to find a more efficient method to this end. In 2004, the MCL algorithm was applied to the localization of mobile WSNs by Hu and Evans for the first time [3]. Baggio proposed the Monte Carlo Localization Boxed (MCB) algorithm, which improves the sampling efficiency to a certain extent by establishing a sampling constraint box [4]. Wang (2007) proposed an adaptive sampling algorithm. Exactly speaking, in the location prediction stage, the number of samples is adjusted according to the area of the anchor box [5]. Hamid and Mehdi proposed a uniform sampling algorithm in the sampling box instead of the random sampling algorithm in MCL, which can effectively avoid the sample points to a region [6]. Rudafshani and Datta (2009) introduced the common neighbor node for the current node localization, and proposed the MSL algorithm. At the same time, this algorithm needs to transmit the sample and weight of the previous moment to the neighbor node, which leads to a large cost in communication [7]. Zhu et al., (2007) used received signal strength indication (RSSI) to calculate the distance between nodes, and then used the distance value for the MCL algorithm [8]. To a certain extent, this algorithm solves the initial positioning accuracy.

In this paper, a new algorithm is proposed to predict the location of mobile nodes by using sector sampling. First of all, this paper introduces the structure and classification of Wireless Sensor Localization Technology. Secondly, the principle of the MCL algorithm is described in detail. Thirdly, we propose an efficient method for mobile node localization based on the MCL algorithm. Finally, the effectiveness and accuracy of the new algorithm are verified by comparative analysis.

2 Wireless sensor network

The WSN is a self-organizing network system which is composed of a large number of micro sensor nodes which in turn are deployed in the monitoring area [9]. There are three kinds of nodes in the WSN, namely the common sensor nodes, the sink nodes, and the management nodes.

After the data acquisition and preprocessing, the wireless sensor nodes transmit the data to the sink nodes through multi-hop routing. Then, the nodes send the data to the remote management center through the Internet for data processing and intelligent processing [10]. Figure 1 shows the architecture of the WSN.

The common sensor nodes have the functions of collecting information, processing data, transmitting data, and cooperating with other nodes. Yet their storage, computing and communication capabilities are relatively weak. To some extent, the advantage of their low power consumption makes up for these defects [11].

The sink nodes are relatively stronger when it comes to processing, storage, and communication. They connect the sensor network and the Internet network, and realize the communication protocol conversion between the two protocol stacks. They are the hub between sensor network and external network [12]. The sink nodes can not only transmit the detected information to the upper network, but can also forward commands from the upper network.

The management nodes consist of a data processing server and monitoring platform [13]. The server has strong data processing ability; it can conduct statistical analyses and provide data support for management. The monitoring platform can display the running state of each node in real time, and can forward various adjustment commands to the sensor network [14].

There are two types of sensor networks according to the mobility of sensor nodes, namely static wireless sensor networks (SWSN) and mobile wireless sensor networks (MWSN). In SWSNs, the location of sensor nodes is fixed, and the node self-localization technology is relatively mature. Corresponding to the SWSN, the node is not static, but moves in real time in the MWSN. So, the location information of the nodes is very important in WSNs [15]. The Global Positioning System (GPS) is a radio navigation and positioning system which has a high precision and mature technology. However, due to the large size of the sensor network area and the huge number of sensor nodes, it is impossible to install a GPS for each node because of the cost and power consumption. Therefore, due to technical needs or costs, the location technology based on WSNs is irreplaceable [16].

Mobile node localization is a technology which can obtain the position information of unknown mobile nodes in real time by technical means. In many papers, the localization algorithms which support mobile location are implemented by the intermittent static positioning algorithm. These methods not only have a large delay, but are also not ideal. Different from the static node localization technology, the localization of mobile nodes requires high real-time performance, which can even be estimated if the anchor nodes are lost.

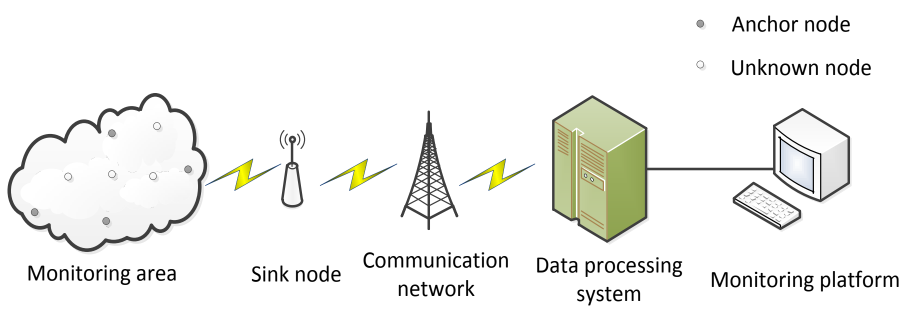

Fig. 1. Figure 1 Architecture of the WSN

3 Basic principles and methods

3.1 Introduction of MCL algorithm

The Monte Carlo method is a kind of processing method which is based on the probability theory, and it can be used to estimate the posterior probability distribution of nonlinear and discrete systems. Exactly speaking, the probability distribution of the research object is estimated by a set of samples with weights. The samples are obtained by importance sampling, and are updated periodically.

In the mobile sensor network localization, the algorithm generally includes initialization, sample selection, and location calculation. The selection of sample points includes prediction and filtering. The flow chart of the MCL is as follows [17].

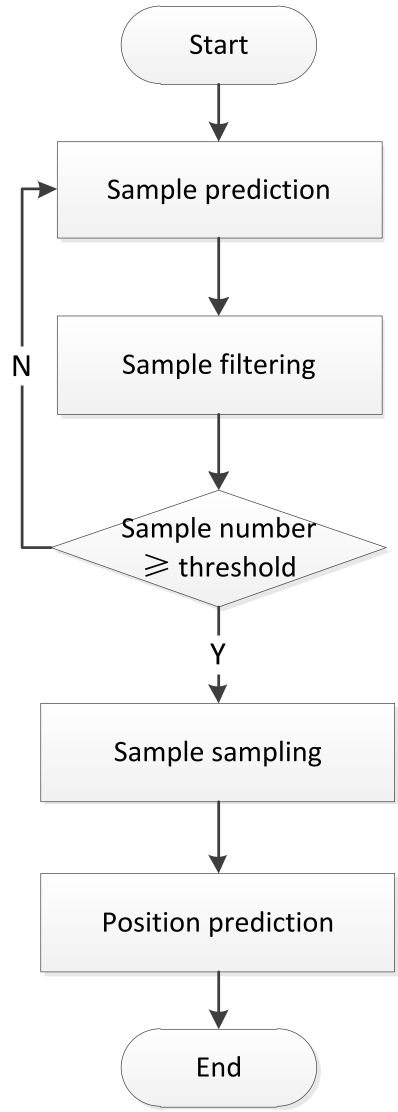

Fig. 2. Flow chart of MCL

3.2 Basic principle of MCL algorithm

Sample prediction: The node location prediction is a method that uses the node information of the last moment *t-1* to predict the location of the current moment. Suppose that the maximum speed of the node is V_{max}, the node position is p_{t-1}, and the node motion model follows the random waypoint model at the last moment, then we can get that the moving node must be in the circle which takes the last location as the center and V_{max} as the radius. The sample prediction area is shown below.

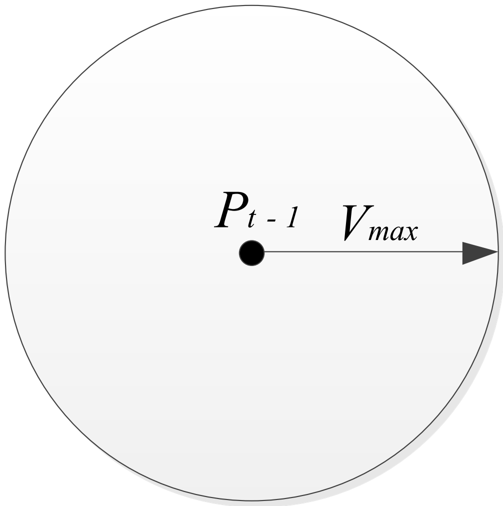

Fig. 3. Sampling area of sample prediction

We define that $l(P_t, P_{t-1})$ is the Euclidean distance between P_t and P_{t-1}, and the node motion obeys uniform distribution [0, V_{max}], then we can get the translation probability density function $M(P_t | P_{t-1})$ as follows.

$$M(p_t^n \mid p_{t-1}^n) = \begin{cases} \dfrac{1}{\pi V_{max}^2} & l(p_t, p_{t-1}) \le V_{max} \\ 0 & l(p_t, p_{t-1}) > V_{max} \end{cases}$$

Filtering stage: The purpose of filtering is to reduce the sample area by removing the sample points which do not meet the requirements. The filtering is carried out by using information obtained from one-hop anchor node and two-hop anchor node. The filter formula is as follows.

$$filter(p) = \begin{cases} s_1 \in S_1 & l(P_t, S_1) < r \\ s_2 \in S_2 & r < l(P_t, S_2) < 2r \end{cases}$$

Where, r is the communication radius of the node, s_1 represents the one-hop anchor node set, s_2 represents the two-hop anchor node set, and $l(P_t, S_1)$ is the Euclidean distance between the anchor node and the sample node p_t. In the one-hop anchor node set s_1, only when $l(P_t, S_1)<r$, are the sample nodes reserved. Otherwise, the nodes will be filtered out. In the two-hop anchor node set S_2, the nodes will be filtered out when $l(P_t, S_1)<r$ or $l(P_t, S_2)<2r$. The shaded part of the following graph is the sample area that meets the filtering conditions.

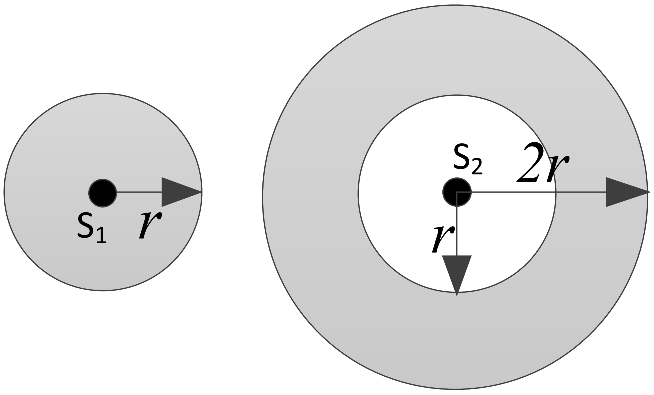

Fig. 4. Sampling area of filtering stage

The sample points are randomly selected in the sample area of the moving node to form the sample set $P_t=\{p_t^0, p_t^1, p_t^2,\ldots p_t^{N-}\}$. If the number of samples is not up to the expected number after the filtering, the system will repeat the prediction and filtering processes again, until the number of samples meets the required sample points.

Position prediction: After the prediction, filtering and sampling, we can get the set of samples. Finally, we can obtain the location information by calculating the average position of these nodes.

$$(x, y) = \left(\frac{\sum_{i=1}^{N} x_p^i}{N}, \frac{\sum_{i=1}^{N} y_p^i}{N}\right)$$

3.3 Main advantages of MCL

The MCL algorithm is a kind of non-ranging distributed algorithm, and it has high positioning accuracy and positioning efficiency compared with other mobile positioning algorithms. It mainly has the following advantages.

1. Simple algorithm structure: Compared with other mobile node localization algorithms, the MCL algorithm needs only to build the correct probability model and calculate the average value of a sample. Therefore, its computational complexity is low.
2. Strong adaptability: The MCL algorithm is based on the theory of the stochastic process, so it is less affected by the external environment, which leads to its strong adaptability.
3. Strong interference: Because the localization error is only affected by sample size and sample standard deviation, the MCL algorithm is not affected by the dimension of the problem.

4 Improved localization algorithm

In the traditional MCL algorithm, the larger the value of V_{max}, the larger the sampling area, and the uncertainty of the node position will increase too. In this paper, the node motion model is constructed to filter the node sample, so as to reduce the possible range of the node and the workload of the prediction, and improve the positioning accuracy of the node.

We assume that the WSN is a two-dimensional plane. At the beginning of the moment, the motion nodes get their true location information according to the MCL algorithm. In addition, each sensor has a memory which stores the location information of the last five moments. We define $t=\{t_0, t_1, t_2, t_3, t_4\}$ as the location variable of the last five moments, and the variables are updated as follows when the mobile node begins to calculate the current location information.

$$\begin{cases} t_0 = t_1 \\ t_1 = t_2 \\ t_2 = t_3 \\ t_3 = t_4 \\ t_4 = (m,n) \end{cases}$$

In two-dimensional space, the vector between point A and point B is obtained by the vector calculation formula as follows.

$$l(A,B) = \frac{yb - ya}{xb - xa}$$

We take the position of t_0 as the center of the circle, so the vectors between the positions of the four moments can be expressed as follows.

$$\begin{cases} l_1 = t_0 t_1 \\ l_2 = t_0 t_2 \\ l_3 = t_0 t_3 \\ l_4 = t_0 t_4 \end{cases}$$

According to the vector angle formula, we can calculate the angle between the two vectors with the following formula.

$$\theta(l_i, l_j) = arccos \frac{l_i * l_j}{|l_i| * |l_j|}$$

Select the maximum angle θ_{max} between four vectors, and we can see that the moving node must be in the sector area which takes t_0 as the center and $l(t_0, t_4)+V_{max}$ as the radius. The sample prediction area is shown in Figure 5.

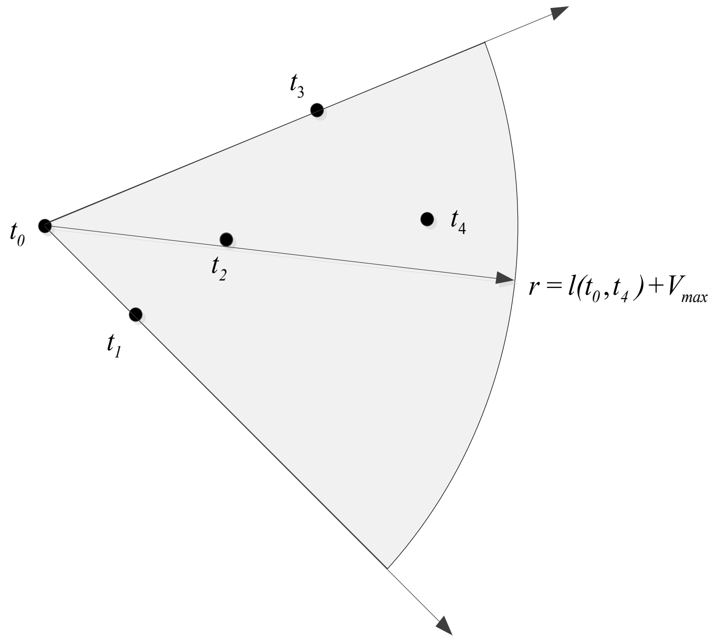

Fig. 5. Sector sampling area of filtering stage

Assuming that the sample area of the MCL algorithm is M, we can get the sample area of the improved localization algorithm as $N=S\cap M$. By sampling the sample points in the sample area, we get $N_t=\{n_t^o, n_t^1, n_t^2,\ldots n_t^{N-1}\}$, and the location of the mobile node can be calculated. The flow chart of the improved algorithm is shown in Figure 6.

Due to the increase in sample prediction, the improved algorithm has a certain degree of increase in the amount of calculation. In spite of this, the computation time of the improved algorithm is not increased. On the contrary, because the improved algorithm filters more invalid nodes, the improved algorithm can reduce the number of repeated sampling and improve the sampling efficiency, which means a reduction in the computation time.

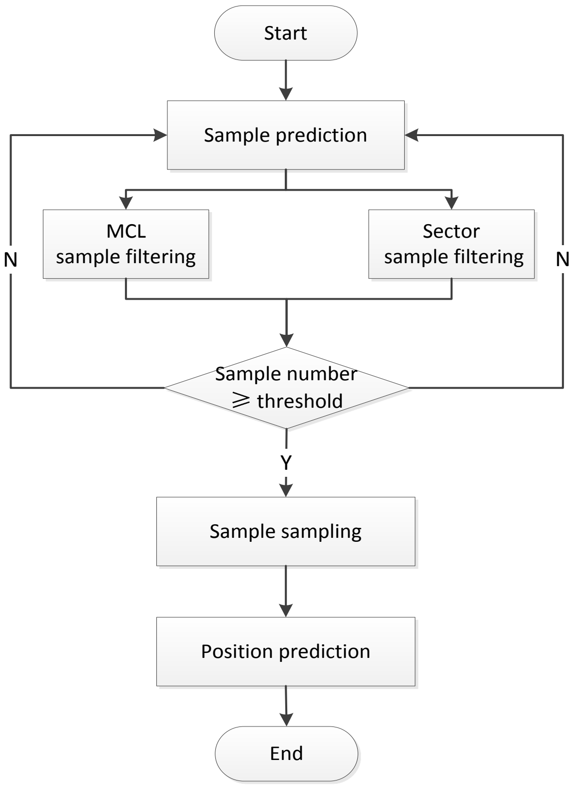

Fig. 6. Flow chart of improved algorithm

5 Simulation and results analysis

In this paper, we use MATLAB as a simulation platform to evaluate the performance of the proposed algorithm. In order to show the performance of the improved algorithm more intuitively, we also conduct experiments on the MCL algorithm. The experimental simulation area is set in the area of $300*300m^2$, and the communication radius of each node is set as $30m$. The specific experimental parameters are shown in Table 1.

Table 1. Simulation parameters

Parameter name	Value
Simulated area	300m*300m
Node communication radius	30m
Minimum number of nodes	50
Maximum number of nodes	180
Minimum movement speed	0.5m/s
Maximum movement speed	3 m/s

Suppose that the number of sensor nodes is W in WSNs, and the number of anchor nodes is V. Then, we can get the number of unknown nodes as W-V. In the end, we can get the formula for average positioning errors as follows.

$$ER = \frac{\sum_{i=1}^{W-V} |s_i - \overline{s_i}|}{W - V}$$

In the above formula, S_i is the estimated coordinates of the moving node, and correspondingly, $\overline{s_i}$ represents the actual coordinates.

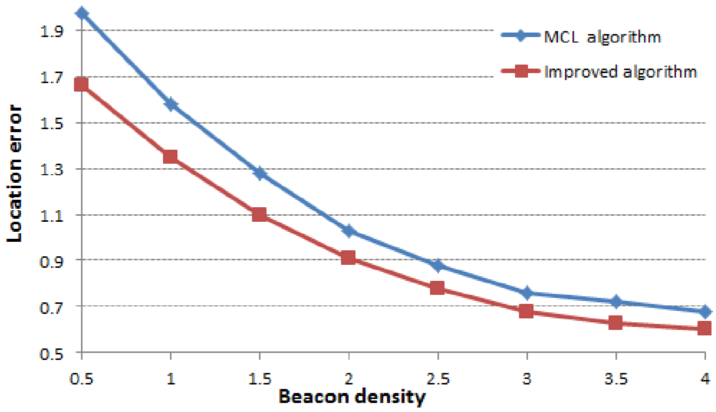

Fig. 7. Node density and location error

Figure 7 shows the effect of the beacon node density on the location error. When the beacon node density is small, the location error of the two algorithms fluctuates greatly. However, with the increase in beacon node density, the error curve tends to be stable. When the beacon node density reaches a certain threshold, no matter how the beacon node increases, there will always be a certain positioning error. Considering the cost of sensor networks, the number of beacon nodes needs to be controlled within a reasonable range.

Figure 8 shows the fluctuation curve of node density and time consumption. When the number of sensor nodes increases, the computation of nodes increases correspondingly, leading to an increase in computing time. Nevertheless, the calculation speed is still relatively small.

Figure 9 shows the effect of node speed on location error. The experimental results show that the positioning accuracy of the mobile node increases and then decreases with an increase in the node speed. On the one hand, the increase in the node moving speed increases the sample area, which leads to a reduction in location accuracy. On the other hand, the mobile node receives more beacon information with an increase in node speed, which can help the node filter out more invalid samples. However, on the whole, the improved algorithm we proposed has a higher accuracy, and it shows more adaptability to node speed.

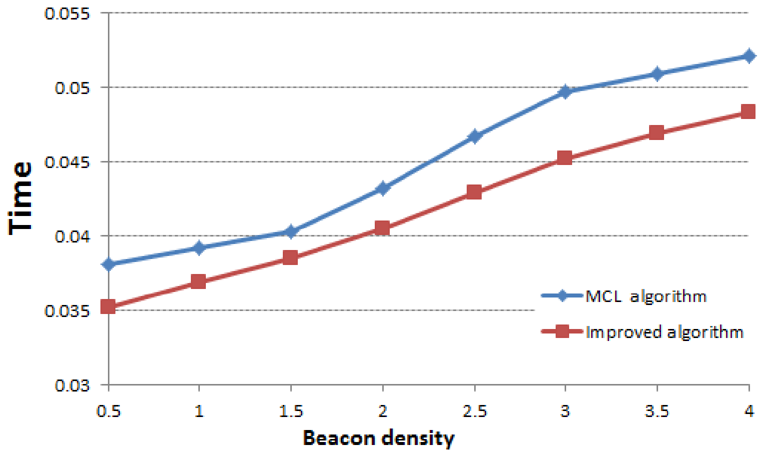

Fig. 8. Node density and time consumption

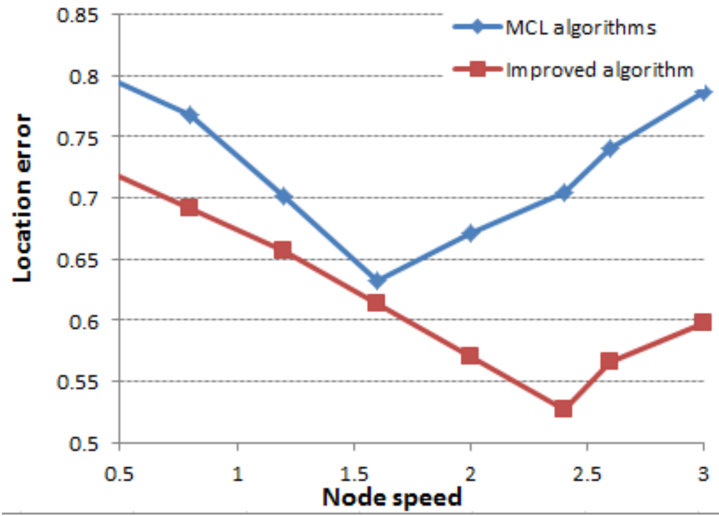

Fig. 9. Node speed and location error

Through the simulation results, we find that the improved mobile node localization algorithm has a certain improvement in time and positioning accuracy. Yet because the positioning accuracy and positioning efficiency are contradictory, we should synthesize various factors to evaluate the performance of a system. Generally, improved positioning accuracy will lead to an increase in positioning time and computational complexity. Therefore, in practical application, we should choose a reasonable location algorithm according to the specific application environment and project requirements.

6 Conclusions

The limited sensor nodes in sensor networks bring great challenges to the localization of mobile nodes. In this paper, a mobile node localization algorithm based on MCL is proposed. By constructing a stochastic motion model, we can improve the positioning accuracy by predicting the motion of nodes and position filtering. Compared with other network location algorithms regarding location time and beacon node density in simulation analysis, we find that the improved mobile node localization method has higher accuracy and higher positioning efficiency in some application scenarios.

For the future research direction on mobile WSNs, we believe that it is also important to shorten the positioning delay and improve the positioning accuracy.

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