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ANALYSIS OF ICSGD AND OSSDL LOCALIZATION ALGORITHMS IN WSN

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ABSTRACT

In our papers before, two three-dimensional localization schemes which are called iterative calculation of secondary grid division localization scheme (ICSGD) and a range free three dimensional optimum space step distance localization scheme (3D-OSSDL) are proposed respectively. In ICSGDLS scheme, forty beacon nodes and five hundred unknown sensor nodes were randomly deployed in a cube, which is divided into smaller cubes twice. The position information of unknown nodes could be got by iteratively calculating the centroid of smaller cubes. However, in 3D-OSSDL algorithm all nodes are randomly deployed in space and forms arbitrary network parameters. By optimizing distances from the network model, the optimum space step distance from nodes to anchors is obtained and the coordinates of all unknown nodes are derived finally. In this paper, comprehensive analysis and comparisons are made by MATLAB software. And by this paper we can find the optimum work status of the two.

Keywords: *WSN, Localization Algorithm, ICSGD, OSSDL*

1. INTRODUCTION

Applications of ANN to power systems are a g in the recent years, localization problem of sensor nodes has been an active research area in Wireless Sensor Networks (WSNs). Position information of nodes is a vital requirement in many WSN applications including monitoring, tracking and geographic routing. Wireless sensor networks significantly differ from classical networks on their strict limitation on energy consumption, simplicity of node processing, and possibly high environmental dynamics.

Until now, many WSN localization schemes have been widely researched, and a large amount of which can be found in [1] and [2], but there is yet much work to do in the field. And so far two main centralized [3-4] and distributed [5-6] localization algorithms have also been proposed. All the general localization mechanisms proposed before can be mainly classified as range-based approaches and range-free approaches. The former approaches determine the node position fully based on distance or angular information acquired using the Time of Arrival (TOA), Angle of Arrival (AOA), Time Difference of Arrival (TDOA), or Received Signal Strength Indicator (RSSI) techniques [7-9]. On the contrary, range-free localization schemes merely rely on the existence of radio connectivity to a neighbor instead of measuring distance or angle to that, which decrease the consumption power and hardware requirements. Range-free schemes mainly explore the local network topology and the coordinate computation is derived from the locations of the surrounding anchor node position coordinates [10].

In this paper, a comprehensive performance analysis of ICSGD and OSSDL are presented to explore their performances. Also comparisons with classic DV-Hop and Centroid algorithms are also made with different simulations under the same simulation environments to better compare them. The index of positioning accuracy is addressed. From simulation results, ICSGD and OSSDL perform better on localization accuracy than others, which is definitely much better than that of original DV-Hop. Also the two are suitable in different environments.

We have done a lot of work in node localization algorithm in WSN. The two algorithms, ICSGD and OSSDL, are both proposed by our work. And simulation results prove that they have better performances.

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The remaining paper is organized as follows: Section 2 describes ICSGD and OSSDL algorithm in detail. Explicit algorithm realizing processes are presented. And performance simulations are made in MATLAB software and simulation results are given in Section 3. We make some conclusions in Section 4.

2. REALIZATION OF ICSGD AND OSSDL

In this scheme, nodes were divided into two categories: beacon node and unknown node. Beacon nodes could get their accurate position information with the help of GPS receivers, while unknown nodes had to calculate their position according to the position of beacon nodes. The beacon nodes could locate themselves accurately by GPS receivers, and they could control transmitting power. The system environment included a number of beacon nodes and unknown nodes. All nodes are randomly deployed in a three-dimensional cube. The localization scheme required some fundamental assumptions as follows:

All nodes were static. Once nodes were randomly deployed, the position of each node was fixed. Each beacon node was equipped with a GPS receiver or some other forms of localization device to get accurate position information. The signal was transmitted in an ideal model, and there was no loss during transmission process. Each node was equipped with omnidirectional antenna, which could receive the signal of all directions.

When an unknown node received the information of beacon nodes, it stored the information into its local information table, which was shown in Table 2. The table included sensor ID, beacon ID and beacon coordinates. After calculation, it also stored the upper limit of layer 1 and layer 2, lower limit of layer 1 and layer 2, first locating coordinates and second locating coordinates into its table which is shown in Figure 1.

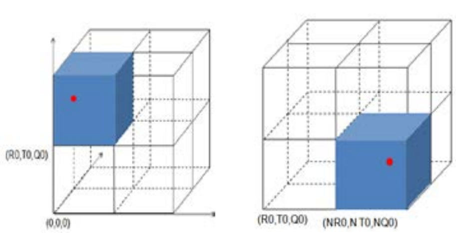

Figure 1. Illustration of grid division

Explain the research chronological, which includes research design, research procedure (in the form of algorithms, Pseudocode or other), how to test and data acquisition [1-3]. The description of the course of research should be supported references, so the explanation can be accepted scientifically [2-4].

Each beacon node broadcast its beacon information in the whole network. At first, it increased its power level according to layer 1, after certain time, it increased power according to layer 2. When an unknown node received its beacon information, stored the information into local information table, and calculated the upper and lower limit of layer1 and layer2, which was shown in Fig.2. With the help of upper and lower limit of layer 1, it could calculate the first coordinates using GDLS. Then, it could calculate the second coordinates according to the upper and lower limit of layer 2 and the first coordinates using GDLS again.

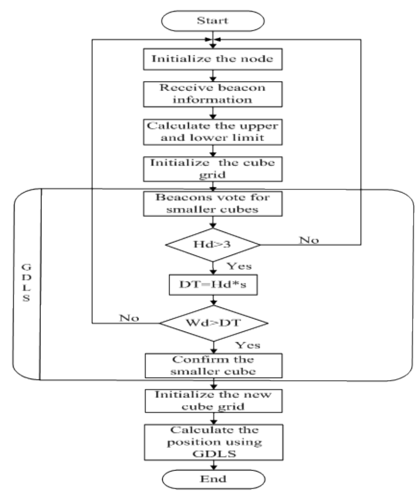

Figure 2. Flow of an unknown node localization

Imagine a sensor node S in 3D space with transmission radius r_0 so that all nodes in the sphere with S as its center are node S's neighbors which is shown in Figure 3. As shown in Figure 3, if a source node S is given, the optimum space step distance toward the destination D at each step is denoted as R_i which is a random variable.

As described in Figure 3, all sensors nodes are deployed in 3D WSN, complying to Poisson distribution with node density $\lambda = \dfrac{N}{L \times L \times L}$. Then, the probability of m sensors located within a sensor's transmission range $Vo(n_i, r_0) = \dfrac{4}{3}\pi r_0^3$ can be expressed as

$$p(m, r_0) = \frac{[\lambda Vo(n_i, r_0)]^m}{m!} e^{-\lambda Vo(n_i, r_0)} = \frac{\left(\frac{4}{3}\lambda \pi r_0^3\right)^m}{m!} e^{-\frac{4}{3}\lambda \pi r_0^3} \qquad (1)$$

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From Figure.3, we can get $V_1 = \frac{2}{3}\pi r_0^3\left(1-\cos\theta\right)$.

Similarly, the probability of m sensors located in a section between (-θ, θ) of a sensor's transmission range is

$$p\left(m,\theta,r_0\right)=\frac{\left(\lambda V_1\right)^m}{m!}e^{-\lambda V_1}=\frac{\left(\frac{2}{3}\pi\lambda r_0^3\left(1-\cos\theta\right)\right)^m}{m!}e^{-\frac{2}{3}\pi\lambda r_0^3\left(1-\cos\theta\right)} \quad (2)$$

Spread the situation depicted above, let x be the distance between S and its next forwarding sensor. x is a random variable, L is virtual value, and the probability of x being less than L can be given as follows.

$$p\left(x\le L\right)=\sum_{m=0}^{N}p\left(m,\theta,r_0\right)p\left(m,\theta,L\right)=e^{-\frac{2}{3}\pi\lambda\left(1-\cos\theta\right)\left(r_0^3-L^3\right)} \quad (3)$$

$$f_x\left(L\right)=\frac{d}{dL}\left(p\left(x\le L\right)\right)=2\pi\lambda L^2\left(1-\cos\alpha\right)e^{-\frac{2}{3}\pi\lambda\left(1-\cos\alpha\right)\left(r_0^3-L^3\right)}\left(0<\alpha<\theta\right) \quad (4)$$

fx(L) above denotes the probability density function of a sensor node locates in the sphere. According to the definition of step distance R, the projection on the line connecting the source and the destination nodes, we get $R = x\cos\theta$. Then the space optimum step distance E(R) can be derived as follows:

$$E\left(R\right)=\frac{\int_0^{\theta}\int_0^{r_0}f_x\left(L\right)L\cos\alpha\, d\alpha\, dL}{\theta} \quad (5)$$

E(R) is an average value. The right side of the equation indicates the integral of angles and distance divides angles. Combining fx(L), we can get the space optimum step distance if the node density λ is given. Of course, λ can be computed under different network parameters.

Distance between any unknown sensor node and anchor node can be computed using Eq. (4) and (5). In our localization scheme, if three distances are gotten, unknown coordinates can be computed accurately. The more accurate the optimum space step distance is, the less the localization error is. The simulation based the localization proposed in this paper are given in the next part.

3. SIMULATION RESULTS

Figure 4 showed the average location error of GDLS and ICSGDLS in a cube of $500^3 m^3$. From it, it could be seen that the average location error decreased as the radio power range of beacon increased. The average location error of GDLS decreased from 0.4308R to 0.2146R as beacon power range increased from 200m to 400m. However, the average location error of ICSGDLS (25+5) decreased from 0.3573R to 0.0692R, and the average location error of ICSGDLS (10+10) decreased from 0.6480R to 0.1306R. Although the cycles of an unknown node in ICSGDLS (25+5) increase by 0.19%, the average location error decreases by 67.7%. The performance of ICSGDLS (10+10) was also better than that of GDLS at a much lower cost when the power range of beacon reached 400m. As shown in Figure 4, the average location error of GDLS could reach 0.2103R in a cube of $20^3 m^3$ when the power range of beacon node was 16m. However, the average location error of ICSGDLS (25+5) could be reduced to 0.0808R.The average location error decreased by 61.6%.

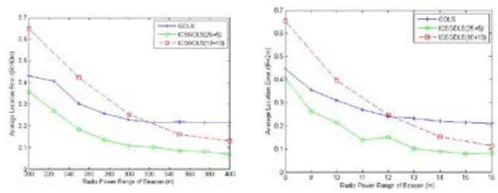

Figure 4. Average location error of GDLS and ICSGDLS in a cube of $500^3 m^3$ *&* $20^3 m^3$

Though the average location error of ICSGDLS(10+10) could only reach 0.1139R, it was acceptable according to its calculation amount.In this scheme, we could select the smaller cube which an unknown node was in after the first division. This avoided dividing the other smaller cubes in the next step, and shrunk the location space. Therefore, amount of calculation could be decreased by a wide margin. In the second division, only the selected cube was divided. As a result, a higher accuracy could be acquired. Through this, the relationship between accuracy and amount of calculation could be dealt with very well.

Simulation had shown the scheme had high accuracy, and the average location error of unknown nodes could reach 0.35m in a cube of $500^3 m^3$. Also, there was no communication between unknown nodes, communication spending could be reduced. Therefore, unknown nodes could make full use of energy they took.The localization of an unknown node was finished by itself, and didn't rely on other unknown nodes. When some unknown nodes were damaged, the other nodes could still be located. Therefore, the scheme was robust.

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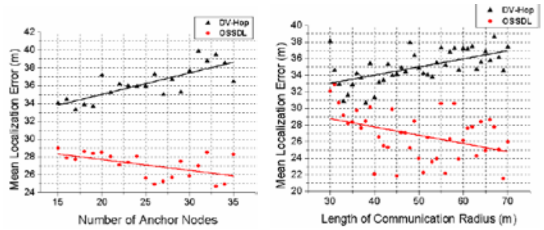

Figure 5. Effects of anchor nodes and communication range

In Figure 5, the number of anchor nodes changes from 15 to 35 with node communication radius 60m and 250 nodes in all in the space region. From the figure, the mean localization error of OSSDL is lower than that of DV-Hop at any number of anchor nodes. When the number of anchor is 26 or 33, differences between them are the most obvious. From the trend line, we can infer that with the increase of the number of anchor, OSSDL performs better and better than DV-Hop propagation. When the radius is less than 40m, OSSDL and DV-Hop is more or less near to each other, but look at the figure in detail, we can find OSSDL is a little more accurate than DV-Hop. Of cause, simulation errors may lead to high inaccuracy which means there will be singular points when simulating. Also from the trend line, we can infer that with the increase of the length of communication radius, OSSDL performs better and better than DV-Hop propagation, too. It is obvious that no matter how many nodes in the network, OSSDL does better than DV-Hop. We can also find some odd nodes in the three figures above inevitably. Although producing odd nodes when simulating, there is no doubt OSSDL optimizes DV-Hop. In the two figures above, DV-Hop both presents a ascending trend which is because in the simulation process, the number of anchor nodes is limited at a small level so underestimation and overestimation when the distance is derived in DV-Hop happens easily which induces a lot of error. Based on Fig.6, Fig.7 and Fig.8, we compute the average error ratios are improved by 26.3%, 22.7% and 28.5%. So results are visible for us.

4. CONCLUSIONS

In this paper, two three-dimensional localization schemes which are called iterative calculation of secondary grid division localization scheme (ICSGD) and a range free three dimensional optimum space step distance localization scheme (3D-OSSDL) are compared.The ICSGD scheme divided the cube twice. During the first division, it selected a smaller cube to decrease the amount of calculation, and decreased the location error in the second division. The scheme could reduce the energy consuming, and it was robust. Through simulation, it was witnessed that ICSGD could achieve higher location accuracy than GDLS at a lower cost in a different space. In the proposed OSSDL scheme, by optimizing distances from the network model accurately with unknown nodes randomly deployed and arbitrarily network parameters, we get the optimum space step distance from nodes to anchors and derive the coordinates of all unknown nodes finally. The simulation results prove the performance of our 3D-OSSDL. Meanwhile, as computing coordinates once 3 distances are received, OSSDL decreases the overload of the whole network.

We found these algorithms cannot be suitable in mobile environment. If we used in mobile nodes, low localization accuracy can be proved. So we will do some researches in mobile environment in the future.

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