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A Novel WSN-Oriented Locating Approach based on Density

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ABSTRACT

It is known that the locating accuracy of the traditional Distance Vector-HOP (DV-HOP) approach in a Wireless Sensor Network (WSN) depends on the density of the anchor node. A novel WSN-oriented locating approach based on a node's density is proposed in this paper. The approach can compute the distance of the node based on the maximum likelihood estimation strategy. It can improve the accuracy ratio of the measuring distance among the nodes. The relative nodes of a WSN can find the average hop distances by estimating the distances from themselves to their circular nodes. In order to assess the performance of the approach, the belief degree of locating is computed based on the possibility theory by our suggested fusion mechanism. This is a feasible method to solve the dependence problem of the DV-HOP algorithm on the anchor node density. Results of many simulation tests of the application show that our proposed WSN-oriented locating approach based on node density can improve the accuracy ratio of the measuring distance and the correctness of locating.

KEY WORDS: Belief degree; density; fusion; error; correctness; estimation

1 INTRODUCTION

THE wireless Sensor Network (WSN) is used as a viable tool in many applications (Zhang & Ge, 2019; Zhang & Wang, 2014). Sensor locating is one of the important problems in a WSN. The antenna arrays of each sensor node or sensor arrays are used to localize the sources (Agaraj, 2012; Zhang, 2012).The basic unit of each sensor includes the transmitting part, the processing part, the power part and the sensing part (Zhang, 2018). It is known that the locating accuracy of the traditional Distance Vector-HOP (DV-HOP) approach in a WSN depends on the density of the anchor node (Zhang, 2012; Zhang & Li, 2014).

As we know, the new positioning or locating technology of the WSN continues to make progress (Guo, 2017; Zhu, 2012). In the positioning or locating application, it often happens that the data, which appears somewhere, is detected by several receiving nodes at the same time (Chen & Mao, 2018; Zhao, 2012). The DV (Distance Vector, such as Ad Hoc DV) method as a kind of positioning or locating technology of a WSN is an on-demand routing service only when the source node and a destination node desire to communicate (BRIDA, 2010; Fan, 2011). There is no "routing loop" by the introduction of the serial number in this approach.

In practice of the DV-HOP approach, the reliable position of the node plays a very important role in collecting data (Liu, 2017; Liu, 2018). In the various fields of using the DV-HOP approach, it is a very important service for the wireless sensor node to locate its position. The location accuracy has high requirements on the number and density of the anchor nodes of a WSN. If the density of the anchor nodes of a WSN reaches a certain amount (such as 88% of the domain), the accurate location can be reached but the cost of the network service is increased, so new efficient algorithms are needed to realize locating for a WSN (Ma, 2017; Kang, 2016). In order to get high reliable locating, some researchers put forward some methods to provide locating and timing service by way of the ranging signals broadcast (Zheng, 2015; Ma & Zhang, 2016).

It is well known that the DV-HOP algorithm designed by Niculescu is a range-free localization algorithm for locating (Niculescu, 2001; Niculescu, 2003). Its main idea is that hop numbers of the nodes

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multiply the average hop distance of each hop to estimate the distance among nodes. The self-estimation algorithm of the hop distance is put forward in the first step using improved DV-HOP algorithms to measure the distance (Zhang & Liu, 2019; Zhang & Tang, 2019). The model of the maximum likelihood estimation is used to assess one-order and two-order hop distances of the each node of a WSN, then by the hop distance ratio to calculate its one-order average hop distance (Zhang & Gao, 2019; Liu, 2018). Based on the belief degree of reliable locating for the improved DV-HOP method is to be evaluated, the improved Dempster-Shafer evidence theory is used (Liang, 2013; Zhang, 2018). Because the sensor node of a WSN being of dynamic evidence has uncertainty, the reliability factor should be considered making a fusion decision for locating (Meng, 2011; Saha, 2007).

According to the above introduction, the relative improvement work was carried out in our new algorithm. A novel WSN-oriented locating approach based on a node's density is proposed in this paper. The approach can compute the distance of the node based on the maximum likelihood estimation strategy.

2 RELATED WORKS

AS the physical hardware of the sensor nodes in a WSN adopts the low specification and low cost to facilitate mass production, it can be intensively applied in monitoring applications (Wang, 2015; Song, 2015). Some researchers (Wang, 2009; Samaras, 2013) investigate locating algorithms, which are based on the received strength, i.e., location fingerprinting (Peng, 2017; Niu, 2017). Some researchers (Wang & Wang, 2009; Song & Wang, 2015) focus on challenges that relate specifically to the location mapping of a WSN. In order to deal with the locating problem with uncertainty for a WSN, some researchers (Wang & Song, 2015; Zhang & Zhang, 2019) adopted the probabilistic logic, Bayesian Network, and D-S Evidence Theory to solve the dynamic location problems.

Two types of nodes exist in a WSN, one is known as the position (anchor node) and the other is the unknown position (normal node). The position of the anchor node is their precise location information obtained from the sensors, BEIDOU or GPS system. The range-based algorithm requires to measure the actual distance or angle information among the nodes, and use three-edges or a multilateral-edges locating method to compute the position of a node (Zhou, 2017; Niu & Liu, 2017). The range-free algorithm adopts the intercommunication of the WSN to estimate the distance between the nodes, and through the three-edges or multilateral-edges locating method to compute the locations of the nodes. The accuracy of the range-based method is higher than that of the range-free but it has higher requirements on the hardware of the nodes. (Kang, 2012; Wang, 2015) studied the optimal filter design method for a class of network stochastic systems. If the system does not need higher accuracy, the range-free method can reduce the cost of setting up a network so the range-free method shows more attention. The typical range-free algorithm has DV-HOP (Niculescu, 2001; Niculescu, 2003), APIT (Wang, 2009), MDS-MAP (Peng, 2017; Zheng, 2016), and so on.

The DV-HOP method is a kind of range-free method and easy to realize (Niculescu, 2001; Niculescu, 2003). The accuracy ratio of the DV-HOP method is affected by the two main aspects; the accuracy ratio of average hop distance and the hop path. As shown in Figure 1, we suppose the sensor nodes are randomly distributed in a W x H rectangular sensing field. Data is sent to the regional central node (cluster head), then transferred to the sink node (Sink).

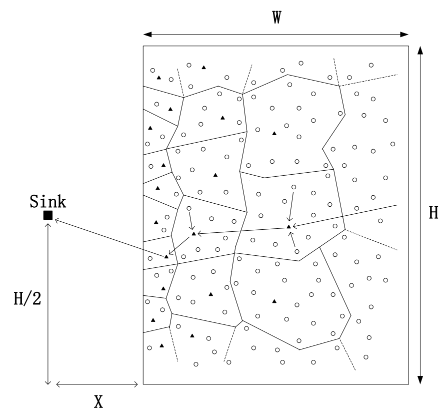

Figure 1. Distribution Map of the Sink and Sensor Node.

Nowadays, many researchers try to improve the locating precision of the DV-HOP algorithm. (BRIDA, 2010; Fan, 2011) presented an improved method by the expected hop distance. The calculated mapping was used in the direction of the normal node and the anchor node to represent expected hop distance and solved the error caused by the loop. (Meng, 2011) reduced the locating error according to the influence of the larger bending path. (Huang, 2012; Du, 2016) studied the influence of the anchor distribution on locating the precision and presented a scheme by the anchor node distribution, and got the optimal node communication radius to improve the location capability. (Peng, 2017), presented a locating method based on extending the anchor node transmission radius to improve the accuracy of locating. (Zhou, 2017; Ma, 2016) applied the EM method to the distance estimation stage but increased the complexity of calculation.

3 MODEL OF LOCATING PROCESS

AS shown in Figure 1, the anchor node and normal node can be randomly deployed in a monitoring region or the ordinary node is randomly dispersed but the anchor node is regularly deployed, which usually is deployed with a triangle or hexagon concern. The first deploy method is adopted in our study. The anchor node obtained itself locating by the BEIDOU or GPS system.

As shown in Figure 2, we suppose that the N node is deployed, and there are K anchor nodes (K N). Ai is the i anchor nodes, and using to represent these nodes coordinates, the residual N - Nk node is unknown nodes. Nodes are deployed randomly in a detecting two-dimensional region where the nodes obey the density λ Poisson distribution. The node transmission radius is R.

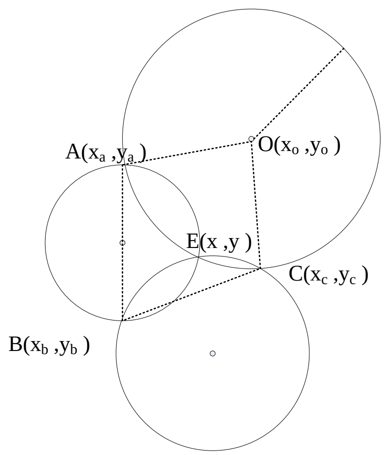

Figure 2. The Two-dimensional Region with Poisson Distribution of the Density.

Lemma 1 Suppose *Θ* is the frame of recognition of a WSN, *U* is a set of individual object space of a given detecting node region *S*, ϕ is an empty set of the node in the WSN, a random function *Bel*: $2^U \to [0, 1]$ is belief function if only if

i) Bel ()=0; ii) Bel (Θ)=1; iii) If X1,X2, …, XnΘ(n is a certain integer) then

$$\mathrm{Bel}\left(\bigcup_{i=1}^{n} X_i\right) \geq \sum_{i=1}^{n} \mathrm{Bel}(X_i) - \sum_{i<j} \mathrm{Bel}(X_i \cap X_j) + \cdots + (-1)^{n+1}\mathrm{Bel}\left(\bigcap_{i=1}^{n} X_i\right) = \sum_{I \subset \{1,2,\ldots,n\}} (-1)^{|I|+1}\mathrm{Bel}\left(\bigcap_{i<I} X_i\right) \tag{1}$$

Proof. The proof of this Lemma 1 can be found in the reference (Liang, 2013).

Lemma 2 Suppose the function *mass* $m_1(\bullet)$, $m_2(\bullet)$ are two basic probability assignment functions in Space *U* of the WSN. *s*, *t* is the focus element set, respectively. Suppose $\sum m_1(s)m_2(t) < 1$, then based on **Lemma 1** and **definition 1**, the following defined function *m*: $2^U \to [0, 1]$ also is a basic probability function.

$$m(X) = \begin{cases} 0 & ,X = \Phi \\ \dfrac{\sum_{s\cap t=X} m_1(s)m_2(t)}{(1-\sum_{s\cap t=\Phi} m_1(s)m_2(t))} & ,X \neq \Phi \end{cases} \tag{2}$$

Proof. The proof of Lemma 2 can be found in the reference (Liang, 2013).

Definition 1 The relative error of the distance estimation was defined as:

$$\mathrm{ErrDis}_{ij} = \frac{|\hat{d}_{ij}\text{- } d_{ij}|}{d_{ij}} \times 100\% \tag{3}$$

where the $\hat{d}_{ij}$ indicates the estimate distance between N_i, N_j. d_{ij} is the actual distance between the two nodes.

The average error of the estimation distance was defined as:

$$\mathrm{Mean}DisErr = \frac{\sum_{i=1}^{Ncount-Bcount}\sum_{j=1}^{Bcount}|\hat{d}_{ij} - d_{ij}|}{R*(Ncount-Bcount)*Bcount} \tag{4}$$

where N_{count} is the number of all nodes, B_{count} is the number of anchor nodes, and *R* is the node radius.

Definition 2 The success rate of localization. The rate of localization is the rate between position nodes of a successfully found grid with the nodes to be measured and all unknown nodes in the region. The result position error rate is defined smaller than $\delta/2$ as the successful position, so the success rate of the localization is as:

$$\mathrm{HitPos} = \frac{\mathrm{Node_{hit}}}{\mathrm{UnNode_{all}}} \times 100\% \tag{5}$$

where $Node_{hit}$ represents the successful locating node and $\mathrm{UnNode_{all}}$ is all unknown nodes.

At the same time, the locating error is defined as:

$$\mathrm{ErrDis}_{ij} = \frac{|\hat{d}_{ij}\text{- } d_{ij}|}{d_{ij}} \times 100\% \tag{6}$$

Among them, $(\hat{x}_i, \hat{y}_i)$ represents the estimated position of unknown node (x_i, y_i).

$$\mathrm{E(ErrPos)} = \frac{\sum_{i=1}^{N} \mathrm{ErrPos_i}}{N} \tag{7}$$

where *N* is the number of the unknown nodes.

4 NEW LOCATING APPROACH BASED ON DENSITY

FIGURE 3 shows the triangulation method. According to formula (10), the distance can be obtained between the two arbitrary nodes, they have public region. The improvement algorithm estimates a certain node with its one-order or two-order node distance. Then, according to one-order or two-order hop distance, the average hop distance is calculated as:

$$DisPerHop_i = \frac{dis_i(NH_{i1})*num_1 + dis_i(NH_{i2})*num_2*2}{num_{i1}+num_{i2}*2} \quad (8)$$

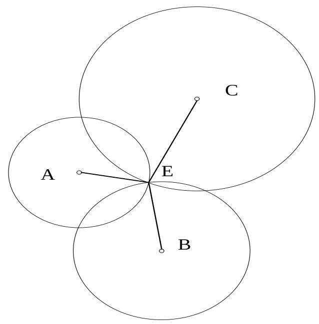

Figure 3. Cases of the Triangulation Method.

Adopting this method can solve the dependence of the traditional DV-HOP algorithm on the number of anchor nodes. In the case of having not much of the anchor nodes, the node average hop distance is related to its surrounding nodes density. In the distance estimated stage, the average value of the average hop distance of two nodes is regarded as the two nodes average hop distance.

$$Distance_{ki} = h_{ki} * (DisPerHop_i + DisPerHop_k)/2 \quad (9)$$

For the same distribution, the error average value is μ, the error value is σ^2. According to the central limit theorem, the node error should obey the normal distribution where the average value is μ and the variance is σ^2/n. Through the measured distance error and analysis experience, the estimated distance error distribution also can be received.

Given N anchor nodes coordinate is (x_i, y_i), i= 1,2,….n, and distance between the anchor node and normal nodes respectively is

$$\begin{cases} (x-x_1)^2 + (y-y_1)^2 = d_1^2 \\ (x-x_2)^2 + (y-y_2)^2 = d_2^2 \\ (x-x_3)^2 + (y-y_3)^2 = d_3^2 \\ \dots\dots\dots\dots \\ (x-x_i)^2 + (y-y_i)^2 = d_i^2 \\ \dots\dots\dots\dots \\ (x-x_n)^2 + (y-y_n)^2 = d_n^2 \end{cases} \quad (10)$$

$$\begin{bmatrix} (x_n - x_1) & (y_n - x_1) \\ (x_n - x_2) & (y_n - x_2) \\ \dots\dots\dots & \\ (x_n - x_i) & (y_n - x_i) \\ \dots\dots\dots & \\ (x_n - x_{n-1}) & (y_n - x_{n-1}) \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} d_1^2 - x_1^2 - y_1^2 - d_n^2 + x_n^2 + y_n^2 \\ d_2^2 - x_2^2 - y_2^2 - d_n^2 + x_n^2 + y_n^2 \\ \dots\dots\dots \\ d_i^2 - x_i^2 - y_i^2 - d_n^2 + x_n^2 + y_n^2 \\ \dots\dots\dots \\ d_{n-1}^2 - x_{n-1}^2 - y_{n-1}^2 - d_n^2 + x_n^2 + y_n^2 \end{bmatrix} \quad (11)$$

It can be expressed as

$$H\,(x, y)^T = P \quad (12)$$

when

$$(x, y)^T = (H^T H) H^T P \quad (13)$$

If two not linear correlation equations are selected randomly, the coordinates of the unknown node can be calculated accurately. The measured distance error is formula (14)

$$\sqrt{(x - x_n)^2 + (y - y_n)^2} = \hat{d}_i + \varepsilon_i \quad (14)$$

This leads to some crossover points of the two circles are not on the third circle.

As shown in Figure 4, the real distance from the anchor nodes of A, B, C to the unknown nodes respectively is d_a, d_b, d_c. The estimated distance respectively is $\hat{d}_a$, $\hat{d}_b$, $\hat{d}_c$ and the error of estimated distance is ε_a, ε_b, ε_c. We use $< B, \hat{d}_b >$ to express circle B as the center, $\hat{d}_b$ as the radius. Thanks to the existence of the range errors, the making intersection point of circle $< B, \hat{d}_b >$, $< C, \hat{d}_c >$, $< A, \hat{d}_a >$ becomes D_1, D_2, D_3. When there are loop effects, the estimated range error will be larger, and the position error will also increase with it.

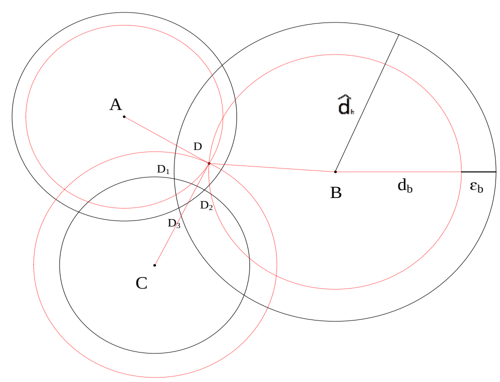

Figure 4. Cases of the Distance Error Analysis.

The crossover point of the arbitrary two circles can be calculated easily. If the result of the measured distance is accurate, then taking an arbitrary equation to draw a circle, which will pass one intersection of the two circles but the measured distance error is existent. There are four kinds of situations between the third circle and the second circle.

Regarding each point as a sample, according to the conjecture intersection density, if finding an area with the intersection point of greatest density, then the coordinates of the points to be measured are in this area. Through the above experiment graph, the density in the focus points is much larger than that of its surrounding points. So we can calculate the coordinates of the points to be measured through the intersection density conjecture. The whole region will be divided into many meshes according to threshold δ, and then calculate the number of the grid nodes. The region with the largest number is the existence of the regional nodes, than it takes the center of the grid as the estimated coordinates. By this method, the estimated position is smaller than $\delta/2$. This calculation can avoid locating errors influenced by a loop.

As shown in the Figure 5, point P1's estimation error is too large, because of the loop. The intersection between the circle with P1 as the center, the estimated distance of $\hat{d}$ as the radius and the other circle are far from the intersection of the dense region. So this algorithm can reduce the effect caused by the large loop distance estimation of any individual node.

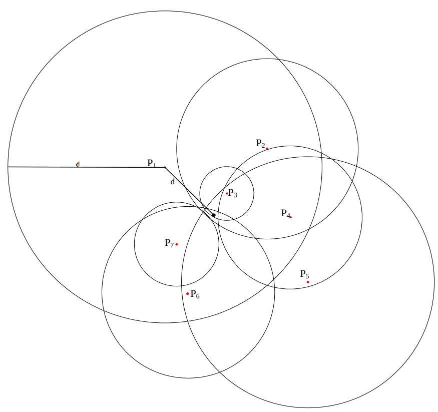

Figure 5. The Effect of the Loop for the Algorithm.

The division of meshing is found that it has a great impact on the location through the experiment. Different divisions have a great influence on the locating accuracy to the same point. The RangeCount ($[x_{min}, x_{max}, y_{min}, y_{max}]$) is defined to calculate the number of the target areas of the intersection. For $[x_{min}, x_{max}, y_{min}, y_{max}]$ of the region with the larger density intersection point, the following parameters are also calculated as formula (15):

$$\begin{cases} num_0 = \text{RangeCount}([x_{min}, x_{max}, y_{min}, y_{max}]) \\ num_1 = \text{RangeCount}\left(\left[x_{min}+\frac{\delta}{2}, x_{max}+\frac{\delta}{2}, y_{min}, y_{max}\right]\right) \\ num_2 = \text{RangeCount}\left(\left[x_{min}, x_{max}, y_{min}+\frac{\delta}{2}, y_{max}+\frac{\delta}{2}\right]\right) \\ num_3 = \text{RangeCount}\left(\left[x_{min}-\frac{\delta}{2}, x_{max}-\frac{\delta}{2}, y_{min}, y_{max}\right]\right) \\ num_4 = \text{RangeCount}\left(\left[x_{min}, x_{max}, y_{min}-\frac{\delta}{2}, y_{max}-\frac{\delta}{2}\right]\right) \\ num_5 = \text{RangeCount}\left(\left[x_{min}+\frac{\delta}{2}, x_{max}+\frac{\delta}{2}, y_{min}-\frac{\delta}{2}, y_{max}-\frac{\delta}{2}\right]\right) \\ num_6 = \text{RangeCount}\left(\left[x_{min}+\frac{\delta}{2}, x_{max}+\frac{\delta}{2}, y_{min}-\frac{\delta}{2}, y_{max}-\frac{\delta}{2}\right]\right) \\ num_7 = \text{RangeCount}\left(\left[x_{min}-\frac{\delta}{2}, x_{max}-\frac{\delta}{2},, y_{min}+\frac{\delta}{2}, y_{max}+\frac{\delta}{2}\right]\right) \\ num_8 = \text{RangeCount}\left(\left[x_{min}-\frac{\delta}{2}, x_{max}-\frac{\delta}{2}, y_{min}-\frac{\delta}{2}, y_{max}-\frac{\delta}{2}\right]\right) \end{cases} \tag{15}$$

The number of intersection points of the nine regions is measured and then takes the maximum. The maximum value of the area is the target area. This way ensures a maximum number of intersections in the largest region for the other division.

The steps of the WSN-oriented locating approach based on the node density are as follows:

(1) Initialize distance vector $\text{dis}(A_1, A_2, \ldots\ldots, A_k)$ from each node to the anchor node, k is the number of anchor nodes. Meanwhile, initialize itself average hop distance with the default value of 1.

(2) Based on node density, the node uses the flooding algorithm to communicate with each other, so that each node can get the hop count of the other nodes and finally forming a Route-Table for the next processing.

(3) For node N_i, according to its current Route-Table, calculate all distances between one-order and two-order neighbor nodes by formula (10) considering the node density. Write this distance into the distance vector $\text{dis}_i(A_1, A_2, \ldots\ldots, A_k)$ and calculate the average hop distance between N_i and DisPerHop_i.

(4) In step (3), if there is a distance vector that cannot be calculated by formula (9), then the remaining distance can be calculated based on the node density.

(5) After node N_i calculates the distance vector $\text{dis}_i(A_1, A_2, \ldots\ldots, A_k)$ by step (3) and step (4), then all circular focus can be calculated by taking N_i as the center and the vector as the radius.

(6) Begin to divide the grid in accordance with δ on the whole region based on the node density, and find the grid, which has the largest number of focus.

(7) Calculate the number of focus on 10 meshes around the grid according to formula (15) and select the grid, which has the largest number of the focus, is as the goal of the grid. Then the center of the grid is the coordinates of the nodes to be measured.

(8) Check the correctness of the above steps according to the threshold of errors. If it is OK, then the game is over, otherwise optimize the above steps based on node density.

When implementing this algorithm, the following three key issues can be solved:

1) The ordinary node no longer obtains the average hop distance of the network through the anchor node but calculates the average hop distance around itself, and uses the average of the average hops of the two nodes as the average hop distance between the two nodes. It can solve the dependence of the traditional Dv-hop algorithm on the number of fixed anchor nodes, reduce the redundancy of the anchor nodes, and thus reduce the data transmission of the network.

2) In order to reduce the influence of the loop on the estimated distance, the circular focus-based localization algorithm is adopted. Since the density of the surrounding focus in the node to be tested is much larger than the surrounding density, it can be solved by the focus-concentration hypothesis to calculate the coordinates of the point. This can reduce the impact of individual nodes due to excessive loop distance estimation and better complete the location.

3) For the same fixed point, the different mesh has a great influence on the accuracy of the location. The

mesh method adopted in this paper can ensure that the number of intersection points in the largest area is the most among the various division methods. Therefore, the accuracy of the location algorithm of this paper is improved.

5 EXPERIMENTAL RESULTS

IN order to study the influence of network parameters on our algorithm, the relationship between the estimate distance accuracy and the network parameters is calculated. The distance estimation error and the position estimation error are also compared for illustrating our algorithm location effect in a WSN. The method in this study is compared with the original DV-HOP (BRIDA, 2010; Meng, 2011) and the LEAP algorithm (Zhou, 2017; Zhang, 2019) based on the expected hop.

First, the dependence is studied on the number of anchor nodes for the distance estimation algorithm with the traditional DV-HOP algorithm. Each aforementioned parameter and its default value in the experiment are as follows: $\hat{d}_{ij}$ =8, d_{ij} =7.5, $ErrDis$ =0.05, Mean$DisErr$ =0.05, R =15, $Ncount$ =120, $Bcount$ =12, HitPos =0.85, $ErrPos_i$=0.04, $ErrPos$=0.05, δ=4.

In order to compare and analyze the improved algorithm, the DV-HOP algorithm and the LEAP algorithm are compared respectively. MATLAB is used to do the simulation experiment. Before the experiment, one hundred nodes are distributed randomly in the 100m * 100m region. Another 100 nodes are also distributed in 200m* 200m region in order to do the distance estimation experiment. Then this program was done in 100m * 100m region to locate the 100 nodes. In the experiments, the nodes can be normal communication with each other. Then according to the different number of the anchor nodes, the localization analysis was done.

Based on **Definition** 1 and **Definition 2**, first of all, the ranging error was analyzed. The analysis can be carried out and the average estimation error obtained through the self-estimate algorithm. Through this algorithm, the distance can be received between the node having the common neighbor node with the anchor nodes and the corresponding anchor nodes from the third step of the improved algorithm, namely the node distance with the jump distance less than 3. In case the radius is respectively 20 and 30, through 20 times of random distribution of the node position, then estimate the average value of the deviation and make a comparison with the DV-HOP algorithm.

Our experimental results show our algorithm has less distance error, but the error also increases as the range increases from this diagram. All distance measures have less deviation than that of the traditional DV-HOP algorithm under the two ranges. When the range increases, the ranging error changes greatly, at the same time, the new ranging method has made the curves reach extreme value when the anchor node reached 15, but the traditional algorithm needs about 23. Therefore our localization algorithm cannot only improve the location precision but also can reduce the distance dependence on the anchor node. It is conducive to control the network cost.

The method proposed in this study is compared with the other three methods in terms of the impact on the number of the anchor nodes and the number of unknown nodes on localization. The four methods to be compared are listed below: 1) the traditional Dv-Distance method (method A) (BRIDA, 2010), 2) improved differential method, Dv-Distance method (method B) (Meng, 2011), 3) the new Dv-distance method based on a path (method C) (Zhou, 2017), and 4) the proposed method in this paper, (method D).

In a WSN, the number of anchor nodes has a significant impact on the positioning accuracy. Under normal circumstances, the more the number of the anchor nodes, the higher the positioning accuracy of the network. However, the cost of the anchor nodes is much higher than the average node cost, so the analysis of the relationship between the number of the anchor nodes and positioning accuracy has great significance. The performance analysis of the method was done in matlab8.0. In the experiment, in the test area, we randomly selected 80 coordinates of unknown nodes, increased the number of the anchor nodes from 5, and the unknown of each anchor node is independent, so that the anchor nodes within the test area follow a Poisson distribution. The experimental parameters about the number of the anchor nodes impacting on the positioning are shown in Table 1.

Table 1. Parameter List.

The area to be a measured range	100m×100m
k value	2
The unknown number of nodes	Randomly generated 80 coordinates
Anchor node number	5-45 increments
Communication radius	30m
The number of experiments	30 times each anchor node

Results are shown in Figure 6 (the effect of the number of the anchor nodes to the positioning precision), when increasing the number of the anchor nodes, positioning from the errors of the four methods are gradually reduced. By mapping, it can be concluded that the proposed method, method D, can have relatively small positioning errors in the same number of the nodes anchor situation. And by analyzing the data of the number of the anchor nodes between 10 and 20, increasing method D of the anchor nodes has a better positioning effect than that of method C, so the method in this work can take full advantage of the increased information of the anchor nodes to improve the positioning accuracy. For the method D curve, the method at the number around 20 of the anchor nodes has already started to slow down its reliance on the anchor node; the positioning accuracy tends to a constant. Thus proving our proposed method based on knowing the circle focal point can improve the utilization of the anchor nodes and get rid of the influence of some anchor nodes to final positioning.

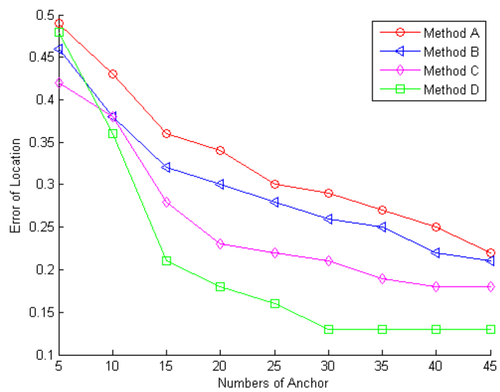

Figure 6. The Effect of the Positioning Precision.

The successful locating rate has been compared among the four algorithms; (the traditional Dv-Distance method (BRIDA, 2010); the improved differential method Dv-Distance method (Meng, 2011); the new Dv-distance method based on the path (Zhou, 2017) and the proposed method in this paper, (method D).

Using the proposed method in this paper, and respectively taking the number of the anchor node of 15, 20, 25, 30, 35, 40, each radius will be done by the 4 tests. According to our experiments, for these, which the locating demand is less than 0.2, the 88.68% successful locating is needed to ensure. The belief degree measure and the locating efficiency can be received when the measuring distance is less than 0.2R is 95%.

6 CONCLUSIONS

A novel WSN-oriented locating approach based on a node's density is proposed in this work. The novel approach can compute the distance of the node based on the maximum likelihood estimation strategy. It can improve the accuracy ratio of the measuring distance among the nodes. The relative nodes of a WSN can find the average hop distances by estimating the distances from themselves to their circular nodes. In order to assess the performance of the approach, the belief degree of locating is computed based on the possibility theory by our suggested fusion mechanism. This is a feasible method to solve the dependence problem of the DV-HOP algorithm on the anchor node density. Results of many simulation tests of the application show that our proposed WSN-oriented locating approach based on the node density can improve the accuracy ratio of the measuring distance and the correctness of locating. The novel approach can be used in the many applications of the WSN, which is helpful for many relative domains.

7 ACKNOWLEDEGEMENT

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8 DISCLOSURE STATEMENT

No potential conflict of interest was reported by the authors.

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