LSDV-Hop: Least Squares Based DV-Hop Localization Algorithm for Wireless Sensor Networks

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Abstract —Wireless Sensor Networks (WSNs) have increasingly become a hot spot of research and application in the fields of computer networks and telecommunications. It is undoubtedly one of the most important issues for WSNs to search an accurate and effective localization method. In this paper, an improved DV-Hop localization algorithm, called least squares DV-Hop (LSDV-Hop), is proposed based on the theory of least squares. LSDV-Hop aims to improve the localization accuracy by extracting a least squares transformation vector between the true and estimated location data of anchor nodes which are randomly chosen. Then, the estimated location data of unknown nodes are updated by the obtained least squares transformation vector, which is helpful to weaken the error of the traditional DV-Hop algorithm. Results of simulation experiments show that the proposed LSDV-Hop method can improve the localization accuracy without increasing the hardware cost for sensor nodes compared with the counterparts.

Index Terms—Wireless sensor networks, Localization, DV-Hop, least squares, quaternion approach

I. Introduction

Localization has always been a hot and key issue for Wireless Sensor Networks (WSNs). During various applications, such as navigation, rescue and environment monitoring, the location information is of great importance to keep the sensed data meaningful and accurate [1]-[2].

Based on whether it needs the actual distance measurement or not, the localization systems can be grouped into two categories: the range-based and the range-free. The range-based algorithms can provide higher localization accuracy. But they are always on the support of special hardware to measure the distances or angles based on the technologies of Received Signal Strength Indicator (RSSI) [3], Time of Arrival (ToA) [4], time difference of arrival (TDoA) [5], time of flight (ToF) [6] or angle of arrival (AoA) [7] to localize the sensor nodes. Therefore, it is costly to employ the range-based algorithms in large scale sensor networks.

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By contrast, the range-free solutions, such as centroid [8], DV-Hop [9], amorphous [10], Approximate Point-in Triangulation TEST (APIT) [11], are more economical and easier to implement. They exploit estimated distances instead of metrical ones to localize the sensor nodes without absolute range information. This inevitably results in less accurate localization but still satisfies the practical applications.

For the purpose of cost conserving in WSNs, we focus on the range-free localization schemes, where one popular and promising algorithm is the DV-Hop method. In its essence, DV-Hop utilizes the one-hop distance to estimate distances between the sensor nodes instead of measuring them by physical devices in the range-based algorithms. Then it relies on the trilateration algorithm or the max likelihood estimator to localize the sensor nodes. The traditional DV-Hop scheme is characterized by computational simplicity, scalable ability and low traffic, but always encounters the problems of loose localization and error accumulation [12].

To achieve accurate localization, some improved DV-Hop algorithms were proposed successfully over the past decade. Reference [13] ameliorated the way of hop-size calculation by averaging the hop-size values of all anchor nodes in the network. It also adopted the 2-D hyperbolic location algorithm to get the final localization results instead of the traditional triangulation algorithm. But its localization accuracy didn't improve too much. Reference [14] proposed a novel algorithm to estimate the average one-hop distance based on weighted disposal. To solve the ambiguous problem of hop-size, reference [16] employed the modified regulated neighborhood distance (RND) method and adaptively adjusted the threshold of packet reception rate to improve the localization accuracy. Reference [17] introduced the Cuckoo Searching (CS) algorithm to correct the localization errors arising in the DV-Hop scheme. In reference [18], the particle swarm algorithm was processed as a parameter optimizer in the ant colony method, and DV-Hop scheme was adopted in the iteration of ant colony.

In this work, aiming at accurate localization, we propose a novel LSDV-Hop solution based on the conventional DV-Hop algorithm and the least squares theory. The major contributions of this work are as follows:

1. The least squares theory is applied into the traditional DV-Hop localization algorithm for the first time to improve the location accuracy of sensor nodes in WSNs without increasing the hardware cost.
2. The real-time update process of LSDV-Hop effectively avoids the error accumulation of traditional DV-Hop algorithm. LSDV-Hop is a novel solution to the problem of inaccurate localization caused by inaccurate distance estimation for the range-free localization system.
3. When the deployment of unknown nodes is altered and that of anchor nodes is unchanged in WSNs (this kind of situation often occurs in practical networks), the least squares transformation vector can be reutilized reasonably. Therefore, LSDV-Hop is an efficient algorithm and it is more suitable for sensor networks of dense nodes and large scale compared with other improved DV-Hop algorithms.

The rest of this paper is arranged as follows. In Section 2 we briefly review the traditional DV-Hop scheme. Section 3 elaborates our proposed LSDV-Hop algorithm. Simulation results and the corresponding analyses are presented in Section 4. Section 5 makes a conclusion and prospects our further efforts.

II. DV-Hop Scheme

DV-Hop is a basic range-free method and it has been one of the most widely applied localization schemes in WSNs. Its implementation process can be simply described by Fig. 1.

Generally, DV-Hop is comprised of three stages:

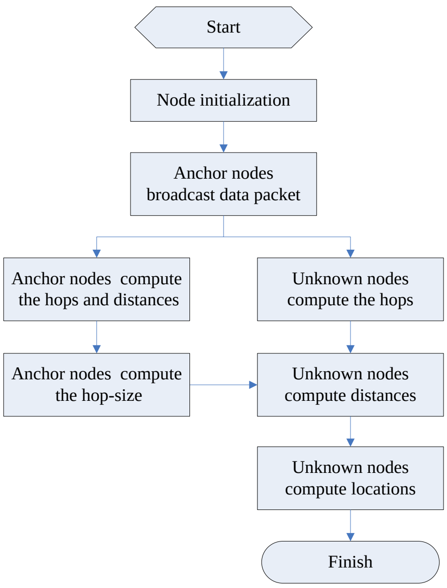

Fig. 1. The implementation process of DV-Hop algorithm

Stage 1. Acquiring the minimum hop-count value

Firstly, each anchor node floods the network with a data packet containing its location and hop-count values initialized to 0. With a classic distance vector exchange protocol, each node in WSNs obtains the hop-count values relative to every another node and maintains the minimum one (referred as hop). Furthermore, each anchor node computes the physical distance relative to every another anchor node by their location information.

Stage 2. Computing the average one-hop distance

Based on the hops and distances obtained in stage 1, anchor node i computes its average one-hop distance (referred as hop-size) by

$$HopSize_i = \frac{\sum_{j\neq i}\sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2}}{\sum_{j\neq i} h_{ij}} \tag{1}$$

where (x_i, y_i) and (x_j, y_j) are the coordinates of anchor nodes i and j, and h_{ij} is the hop between them $(i, j = 1, 2, ...N)$, where N denotes the number of anchor nodes in WSNs.

Then each anchor node broadcasts its hop-size to the whole network. Each unknown node whose location is undetermined receives the hop-size information and only maintains the one it first receives. By multiplying the hop-size by the hop, each unknown node k can calculate out its physical distance to the anchor node i:

$$d_{ik} = HopSize_i \cdot h_{ik} \tag{2}$$

where $k = 1, 2, ..., M$ and M denotes the number of unknown nodes in WSNs. h_{ik} presents the hop between anchor node i and unknown node k.

Stage 3. Computing location

After obtaining the physical distances to the anchor nodes, each unknown node can perform the trilateration or max likelihood estimation algorithm to get its own location in the network.

III. LSDV-Hop Localization Algorithm

From the above description of the traditional DV-Hop scheme, it can be seen that multiplying the imprecise hop-size by the hop to replace the real distance may cause large error of distance estimation. Inaccurate distance estimation eventually results in inaccurate localization.

Aiming to achieve accurate localization, LSDV-Hop extracts a transformation vector between the true and estimated location data of the anchor nodes based on the least squares theory. The estimated location data of unknown nodes are updated then by the obtained least squares transformation vector to weaken the error of the traditional DV-Hop algorithm. The overall structure of our LSDV-Hop algorithm is shown in Fig. 2. It is mainly composed of three newly added parts in addition to the basic DV-Hop algorithm: anchor nodes division, least squares transformation and transformation update.

A. Anchor Nodes Division

Firstly, all the N anchor nodes are divided into two parts according to the stochastic rule: N_1 AnchorNodes1 and N_2 AnchorNodes2 with N_1+N_2=N. In Fig. 2, X_{AN}, X_{AN1} and X_{AN2} denote the true values of the sensor nodes' location respectively. Then both of AnchorNodes1 and AnchorNodes2 are fed into the traditional DV-Hop algorithm with AnchorNodes1 serving as the anchor nodes and AnchorNodes2 as the unknown nodes. At last we can get the estimated location $\hat{X}_{AN2}$ of AnchorNodes2.

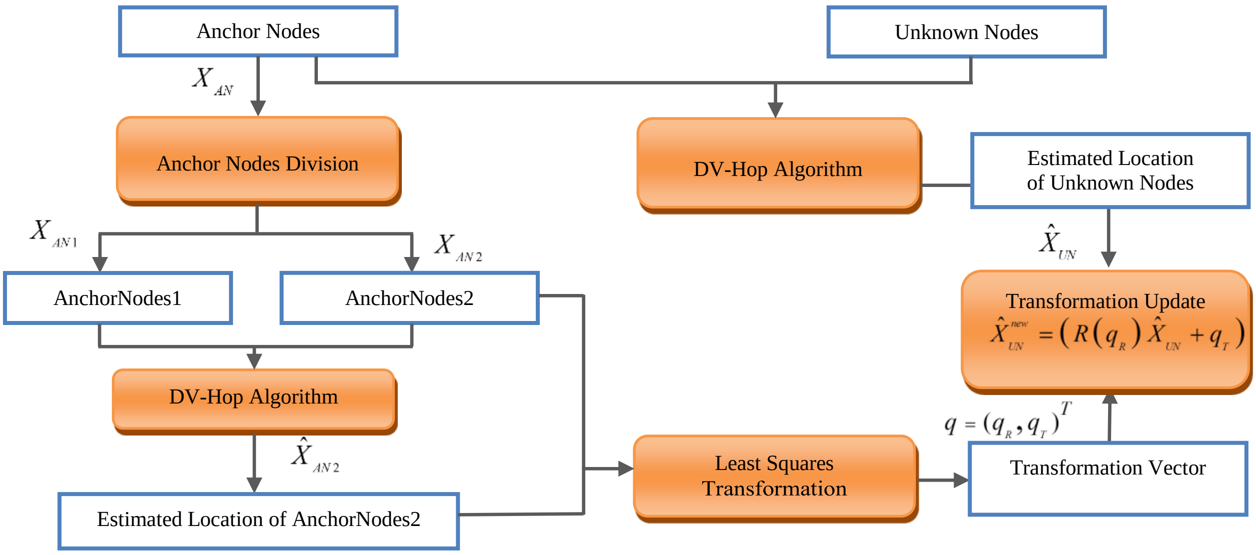

Fig. 2. The overall structure of LSDV-Hop algorithm

B. *Least Squares Transformation*

As the estimated location of AnchorNodes2 $\hat{X}_{AN2}$ has been obtained and its true value X_{AN2} is also known, we can find a least squares transformation vector between $\hat{X}_{AN2}$ and X_{AN2}. Here we can use the quaternion approach to yield the least squares transformation vector which is composed of a rotation matrix and a translation matrix [19].

Let $q_R=\begin{bmatrix}q_0 & q_1 & q_2 & q_3\end{bmatrix}^T$ be a unit rotation quaternion vector, where $q_0^2+q_1^2+q_2^2+q_3^2=1$ and $q_0 \geq 0$. Then the 3×3 rotation matrix $R(q_R)$ generated by the above unit rotation quaternion vector q_R can be represented as:

$$R\left(q_R\right)=\begin{bmatrix} q_0^2+q_1^2-q_2^2-q_3^2 & 2\left(q_1q_2-q_0q_3\right) & 2\left(q_1q_3+q_0q_2\right) \\ 2\left(q_1q_2+q_0q_3\right) & q_0^2+q_2^2-q_1^2-q_3^2 & 2\left(q_2q_3-q_0q_1\right) \\ 2\left(q_1q_3-q_0q_2\right) & 2\left(q_2q_3+q_0q_1\right) & q_0^2+q_3^2-q_1^2-q_2^2 \end{bmatrix} \tag{9}$$

Let $q_T=\begin{bmatrix}q_4 & q_5 & q_6\end{bmatrix}^T$ be a translation vector. Then the whole transformation vector can be expressed as $q=\left[q_R, q_T\right]^T$.

Given X_{AN2}^l and $\hat{X}_{AN2}^l$ be the true and estimated locations of the AnchorNodes2 l, respectively, the mean square error function to be minimized is

$$f(q)=\frac{1}{N_2}\sum_{l=1}^{N_2}\left\|X_{AN2}^l-\left(R(q_R)\hat{X}_{AN2}^l+q_T\right)\right\|^2 \tag{10}$$

where $l=1,\ldots N_2$.

Let μ_{AN2} and $\hat{\mu}_{AN2}$ denote the centers of the true and estimated locations of the AnchorNodes2 l, respectively, then

$$\mu_{AN2}=\frac{1}{N_2}\sum_{i=1}^{N_2}X_{AN2}^l \tag{11}$$

$$\hat{\mu}_{AN2}=\frac{1}{N_2}\sum_{i=1}^{N_2}\hat{X}_{AN2}^l \tag{12}$$

The cross covariance matrix P of μ_{AN2} and $\hat{\mu}_{AN2}$ is given by

$$P=\frac{1}{N_2}\sum_{i=1}^{N_2}\left(X_{AN2}^l-\mu_{AN2}\right)\left(\hat{X}_{AN2}^l-\hat{\mu}_{AN2}\right)^T \tag{13}$$

The cyclic components of the anti-symmetric matrix are used to form the column vector $\Delta=\begin{bmatrix}\Lambda_{23} & \Lambda_{31} & \Lambda_{12}\end{bmatrix}^T$. This vector is then used to form the symmetric matrix Q:

$$Q=\begin{bmatrix} tr\left(P\right) & \Delta^T \\ \Delta & P+P^T-tr\left(P\right)I_3 \end{bmatrix} \tag{14}$$

where I_3 is the 3×3 identity matrix.

The unit eigenvector $q_R = [q_0 \quad q_1 \quad q_2 \quad q_3]^T$ corresponding to the maximum eigenvalue of the matrix Q is selected as the optimal rotation vector. And the optimal translation vector q_T is given by

$$q_T = \mu_{AN2} - R(q_R)\hat{\mu}_{AN2} \tag{15}$$

C. Transformation Update

From formula (10) we can see that the rotation matrix q_R and translation matrix q_T obtained above can minimize the mean square error between the true and estimated locations of the anchor nodes. The unknown nodes and the anchor nodes are deployed in the same network situation. In the sense of mathematics, the unknown nodes and the anchor nodes belong to different sets of points but they share the same properties. Consequently, if we use the least squares transformation vector $q = [q_R, q_T]^T$ extracted from the anchor nodes to update the estimated location $\hat{X}_{UN}$ of the unknown nodes, the updated value of $\hat{X}_{UN}$ will match its true value much better. It is worth mentioning that the estimated location $\hat{X}_{UN}$ of the unknown nodes is also obtained from the traditional DV-Hop algorithm. The transformation update process can be described by the following formula:

$$\hat{X}_{UN}^{new} = \left(R(q_R)\hat{X}_{UN} + q_T\right) \tag{16}$$

where $\hat{X}_{UN}^{new}$ denotes the newly corrected value of $\hat{X}_{UN}$ by the least squares transformation vector.

IV. Simulation and Algorithm Analysis

In order to test the localization accuracy of our LSDV-Hop algorithm, we use the random distribution network topology with 100 sensor nodes in the region of 100m×100m. All algorithms are implemented in Matlab and executed on 1.50GHz Intel® Core(TM)2 CPU T5250 with RAM of 2GB.

During the following simulation, algorithms' localization accuracy is evaluated by the localization error rate which can be computed by

$$E = \frac{X_{UN} - \hat{X}_{UN}}{R} \tag{17}$$

where R is the communication radius of the sensor nodes, here we assume R of all nodes are identical. The final result is averaged by random test of 200 times.

A. Selection of Communication Radius

The hop-count value and hop-size among the sensor nodes of WSNs mainly depend on the nodes' communication radius R. Therefore, we firstly explore the influence of different communication radius on the localization accuracy and select the optimal radius. In this simulation, the number of anchor nodes N is 20 and the anchor node division ratio is set as 1:1.

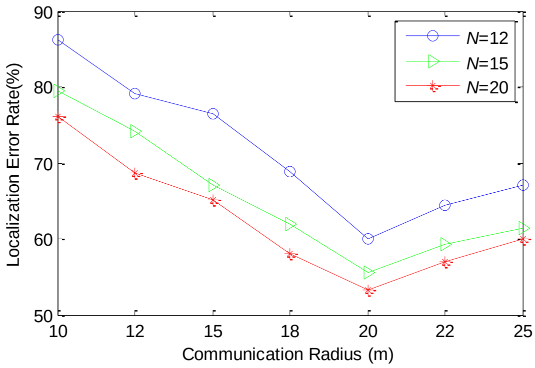

Fig. 3. The impact of communication radius on the localization error rate

Fig. 3 shows the relationship between localization error rate and communication radius when the number of anchor nodes N is 12, 15 and 20 respectively. It can be obviously seen that the communication radius has an optimal value of 20m. When the communication radius becomes smaller, communications among anchor nodes get even worse, thereby leading to poorer localization performance of unknown nodes. When the communication radius gets larger, some unknown nodes are located to be the same node, which will cause larger error. As a result, larger or smaller communication radiuses induce the increase of localization error rate. In the following tests, the communication radius is set as 20m.

B. Selection of Division Ratio of Anchor Nodes

In the first step of our LSDV-Hop algorithm, all the N anchor nodes are divided into N_1 AnchorNodes1 and N_2 AnchorNodes2 with $N_1+N_2=N$. Then we will probe the effect of different division ratio N_1:N_2 of anchor nodes to the localization accuracy.

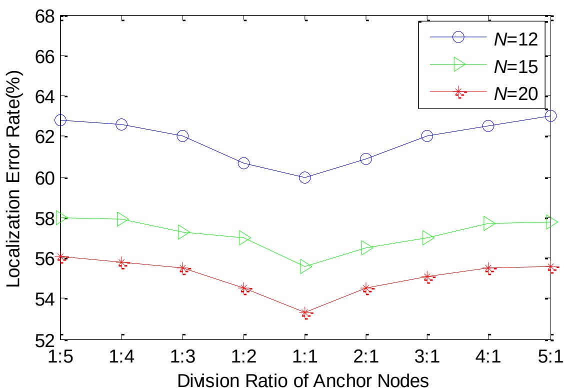

Fig. 4. The impact of division ratio of anchor nodes on the localization error rate

Fig. 4 shows the relationship between localization error rate and anchor node division ratio when the number of anchor nodes N is 12, 15 and 20 respectively. From the figure we can see that each curve of localization error rate changes in the range of 3% with different anchor node division ratio. It illustrates that the impact of anchor node division ratio on the localization accuracy is not too much. However, when the division ratio is 1:1, we can obtain the best localization accuracy. Therefore, the anchor node division ratio is selected as 1:1 in the following tests.

C. Performance Comparison of Localization Accuracy

In order to illustrate the effectiveness of our new algorithm, it is necessary to make comparisons with the counterparts. Here we choose the original DV-Hop method (referred as DV-Hop), the improved DV-Hop algorithm in reference [13] (referred as Method I), the weighted DV-Hop algorithm in reference [14] (referred as Method II) and the latest IWC-DV-hop algorithm in reference [15] (referred as Method III) for comparison.

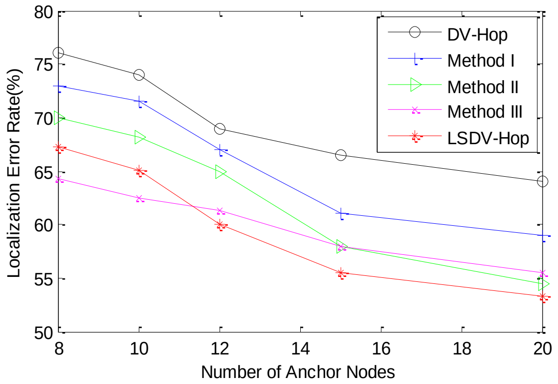

Fig. 5. Localization accuracy under different number of anchor nodes

The localization accuracy under different number of anchor nodes is presented in Fig.5. It can be found that our proposed LSDV-Hop algorithm has the best localization accuracy compared with the counterparts. The localization error rate averagely reduces by about 9.48%, 5.98%, 3.85% and 1.05% compared with the original DV-Hop, Method I, Method II and Method III.

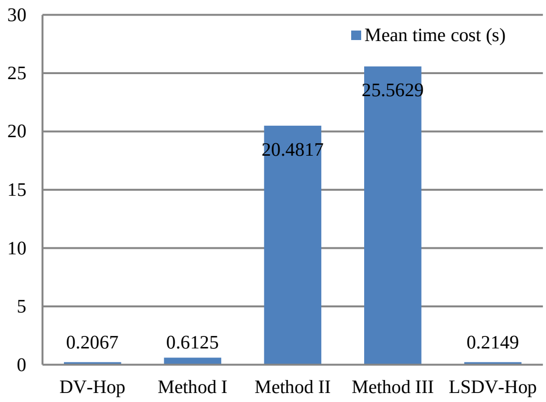

Fig. 6. Performance comparison of mean time cost.

D. Performance Comparison of Computation Time

The mean values of computation time for DV-Hop, Method I, Method II, Method III and LSDV-Hop are compared in Fig. 6 for further evaluation. Due to the employment of 2-D hyperbolic location algorithm, the mean time cost of Method I is about 0.4s longer than that of the original DV-Hop algorithm. Furthermore, the running time of Method II is approximately 100 times longer than that of DV-Hop, because Method II must search three anchor nodes randomly to perform the trilateration. While Method III takes the longest time due to the introductions of threshold distance and weighted centroid algorithm. However, LSDV-Hop spends almost the same time as the original DV-Hop algorithm. It guarantees that the proposed LSDV-Hop approach could outperform the counterparts at a much faster speed.

E. Performance Comparison of Memory Overhead

Despite the computation time cost, algorithms will also introduce additional memory overhead on sensors. In this simulation, we give comparisons of the mean memory overhead for DV-Hop, Method I, Method II, Method III and LSDV-Hop in Fig. 7. It can be seen that our LSDV-Hop has almost the same memory cost as the original DV-Hop method, and its memory overhead is fewer than the other three methods.

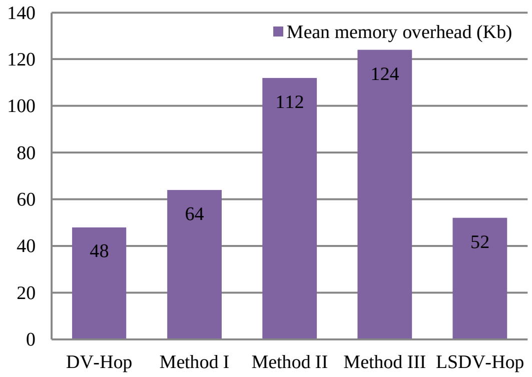

Fig. 7. Performance comparison of mean memory overhead.

V. Conclusions

This paper presented an improved DV-Hop algorithm based on the least squares theory. The simulation results demonstrated that our proposed LSDV-Hop algorithm has a better performance in terms of localization accuracy than the original DV-Hop method and the other three improved DV-Hop algorithms. When the deployment of unknown nodes is altered and that of anchor nodes is unchanged in WSNs (this kind of situation often occurs in practical networks), the least squares transformation vector can be reutilized reasonably. Therefore, LSDV-Hop is an efficient algorithm and it is more suitable for sensor networks of dense nodes and large scale compared with other improved DV-Hop algorithms. In the future, we plan to explore the other improvements and incorporate them into the LSDV-Hop algorithm.

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