Spatial Crowdsourcing-Based Sensor Node Localization in Internet of Things Environment

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Abstract. With the development of mobile computing, sensor technology and wireless communications, Internet of Things (IoT) has been one of the research hotspots in recent years. Because sensor node localization plays an important role in IoT, we propose a spatial crowdsourcing-based sensor node localization method in this paper. Based on the concept of spatial crowdsourcing, anchor nodes are assigned to new locations according to node location relationship for localization performance improvement. Then, unknown nodes are upgraded to be anchor nodes. Finally, localization coordinates are calculated with DV-Hop method. Simulation results prove that our proposed localization method outperforms DV-Hop method.

Keywords: IoT · Spatial crowdsourcing · Localization
Node upgradation

1 Introduction

Internet of Things (IoT) can be defined as a network of Internet-connected objects and is able to exchange data with sensors [1]. Based on Internet technology, IoT is developed as an extension and expansion of Internet, through which clients and objects are connected. Therefore, information acquisition and fusion have been the key technologies in IoT. Meanwhile, perceptions, recognition and other functions are mainly finished by sensor nodes, so the sensing layer of IoT that consists of sensor nodes is a necessary component [2,3].

In most scenarios, location information of sensor nodes is needed and makes the collected data meaningful. Therefore, sensor node localization plays an important role in IoT. Generally, localization methods can be divided into two classes: range-based and range-free localization methods. So far, many localization methods have been proposed for sensor node localization such as trilateration method, DV-Hop method and centroid method [4,5]. Meanwhile, machine learning and intelligent optimization algorithms are also applied for localization performance improvement [5–7].

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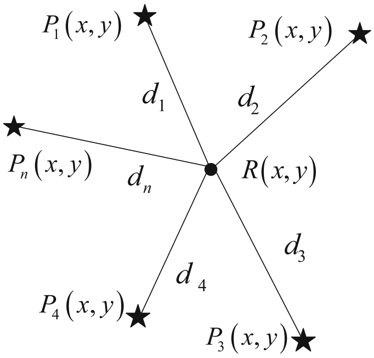

Fig. 1. Maximum likelihood method.

Recently, crowdsourcing has been an emerging concept. Crowdsourcing is the process of getting work or funding from a crowd of people online. The development of mobile computing and sensor technology has enhanced the capability of crowdsourcing [8]. As one of the crowdsourcing technologies, spatial crowdsourcing opens up a new mechanism for spatial tasks. These tasks are assigned according to workers' locations [9]. Based on the concept of spatial crowdsourcing, we try to apply spatial crowdsourcing to sensor node localization in order to achieve a better localization performance.

In this paper, we use a small number of anchor nodes to locate unknown nodes. In particular, we focus on the application of spatial crowdsourcing for sensor node localization in IoT and the influence of the anchor node locations on localization accuracy. In addition, unknown nodes are located and can also be upgraded to be new anchor nodes. Through simulation, we analyze the performance of our proposed localization method. Our proposed method is effective in reducing localization errors of sensor nodes in IoT.

The remainder of this paper is organized as follows: we review the related works in Sect. 2. The proposed localization method is described in detail in Sect. 3. The simulation results and analyses are given in Sect. 4. Finally, Sect. 5 concludes this paper.

2 Related Works

2.1 Maximum Likelihood Method

Maximum likelihood method is developed from trilateration method. Although trilateration method is simple, when the intersection of three circles cannot meet at one point, it is difficult to obtain accurate localization coordinates [5]. With multiple anchor nodes, we exploit maximum likelihood method in this paper. Through solving localization equations, we can get the location coordinates of an unknown node. Assume the distances between an unknown node $R(x, y)$ and nearby anchor nodes $P_1(x_1, y_1), P_2(x_2, y_2), \cdots, P_n(x_n, y_n)$ are $d_1, d_2, \cdots, d_n$, respectively. The adopted maximum likelihood localization method is shown in Fig. 1. According to the measured distances between nodes, the localization equations can be given by:

$$\begin{cases} (x-x_1)^2+(y-y_1)^2=d_1^2 \\ (x-x_2)^2+(y-y_2)^2=d_2^2 \\ \cdots \\ (x-x_n)^2+(y-y_n)^2=d_n^2 \end{cases} \tag{1}$$

Then the equations are solved and location coordinates can be denoted by:

$$\boldsymbol{X}=\left(\boldsymbol{A}^{\mathrm{T}}\boldsymbol{A}\right)^{-1}\boldsymbol{A}^{\mathrm{T}}\boldsymbol{B} \tag{2}$$

where $\boldsymbol{X}=\begin{pmatrix} x \\ y \end{pmatrix}$; $\boldsymbol{B}=\begin{bmatrix} x_1^2-x_n^2+y_1^2-y_n^2+d_n^2-d_1^2 \\ \vdots \\ x_{n-1}^2-x_n^2+y_{n-1}^2-y_n^2+d_n^2-d_{n-1}^2 \end{bmatrix}$;
$\boldsymbol{A}=\begin{bmatrix} 2(x_1-x_n) & \cdots & 2(y_1-y_n) \\ \vdots & \ddots & \vdots \\ 2(x_{n-1}-x_n) & \cdots & 2(y_{n-1}-y_n) \end{bmatrix}$. Therefore, the location coordinates of unknown node $R(x,y)$ can be estimated.

2.2 DV-Hop Localization Method

DV-Hop method is considered as a distributed localization method with high localization accuracy [10]. First, this method needs to know the number of hops and distances between nodes, then the target node can be located. The method is divided into three steps as follows:

Step 1: Each anchor node carries location data, with which hop number can be estimated. Assume the communication radius is r and distance between nodes is d, then the hop number is estimated. As shown in Fig. 2, if r is larger than d, one hop is needed. If r is smaller than d, two hops are needed.

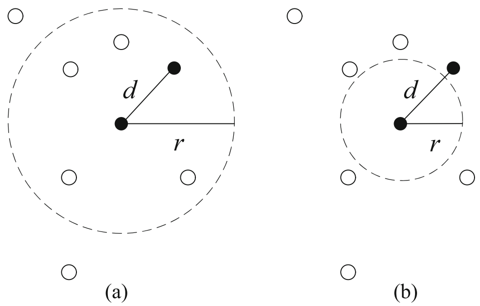

Fig. 2. Calculation of hop number with different r: (a) r is larger than d, (b) r is smaller than d.

Step 2: Through communications among these nodes, the distances between anchor nodes can be calculated, which are also obtained by other nodes. Then the average hop distance can be calculated by:

$$\bar{d} = \frac{\sum_{j \neq i} \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}}{\sum_{j \neq i} h_j} \tag{3}$$

where (x_j, y_j) represent the coordinates of anchor node j; (x_i, y_i) represent the coordinates of anchor node i; h_j represents the hop number of anchor node j to anchor node i; $\bar{d}$ is the mean hop distance.

Step 3: When the distance information is available to other nodes, the maximum likelihood method mentioned above is performed to calculate the final localization coordinates. In this paper, localization methods are compared with mean error, which can be calculated as follows:

$$e = \frac{\sum_{i=1}^{N} \sqrt{(X_i - x_i)^2 + (Y_i - y_i)^2}}{N} \tag{4}$$

where (x_i, y_i) are the localization coordinates of node i; (X_i, Y_i) are the real coordinates of node i; e is the mean error.

2.3 Influence of Anchor Node Location on Localization Performance

Because if the coverage area of each anchor node is too large, the node resource will be wasted [11]. Thus, we need to adjust the locations of anchor nodes to enlarge the coverage area without overlap and also improve localization performance. When anchor nodes have the same radius, the ideal location relationship is that the intersect point is at the center of the triangle as shown in Fig. 3. At this time, the circle covers the larger area and better localization performance can be achieved [12]. In this paper, we applied spatial crowdsourcing to

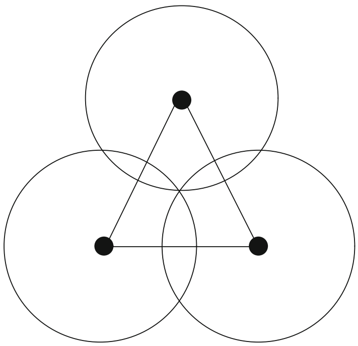

Fig. 3. Node location relationship.

sensor node localization. The locations of anchor nodes are adapted by spatial crowdsourcing to improve localization accuracy.

3 Proposed Localization Method

In this paper, we proposed a spatial crowdsourcing-based sensor node localization method that mainly has four steps: node movement, node selection, node upgradation, and DV-Hop localization. The flow chart of the proposed method is shown in Fig. 4.

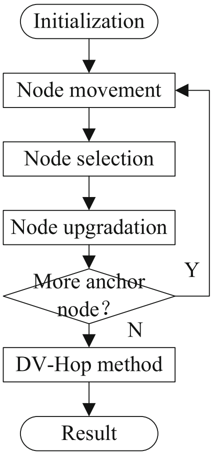

Fig. 4. Flow chart of the proposed method.

Assume the initial set of unknown nodes is $\boldsymbol{R} = \{R_i\left(x_i, y_i\right) | i = 1, 2, \cdots, N\}$ and the initial set of original anchor nodes is $\boldsymbol{P} = \{P_i\left(x_i, y_i\right) | i = 1, 2, \cdots, M\}$, in the beginning, anchor node $P_i(x_i, y_i), i \in \{1, 2, \cdots, M\}$ moves from location (x_i, y_i) to location (x_i', y_i') based on spatial crowdsourcing in order to compute a more accurate localization result. Then an unknown node is selected and upgraded to be a new anchor node. So the new set of anchor nodes can be denoted as $\boldsymbol{P'} = \{P_1\left(x_1, y_1\right), P_2\left(x_2, y_2\right), \cdots, P_M\left(x_M, y_M\right), R_i\left(x_i, y_i\right)\}$. In this paper, the node with minimum localization error is selected and upgraded. Although this selection method is not very practical, how to select nodes for upgradation is not concentrated in this paper. If more nodes are needed to be upgraded, then the original anchor nodes in set $\boldsymbol{P}$ move again based on spatial crowdsourcing. If not, then localization coordinates are calculated with DV-Hop method.

4 Experimental Results and Analyses

4.1 Experimental Setup

In this paper, we first set the node distribution area and randomly distribute the nodes. The node distribution area is a square area with dimensions of 100 m × 100 m. We let the numbers of anchor nodes and unknown nodes be 10 and 90, respectively, and the communication radius be 50 m. In this scenario, the mean error of sensor node localization with DV-Hop method is 34.51 m. The initial distribution of all the nodes is shown in Fig. 5.

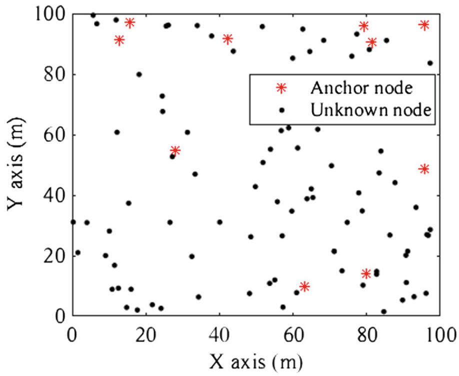

Fig. 5. Node initial distribution.

4.2 Localization Results with Anchor Nodes at Different Locations

As shown in Figs. 6 and 7, a simple example of node location influence on localization performance is given. We generate four nodes randomly. Three of them are anchor nodes and the other one is an unknown node. At first, the localization error is 16.53 m. One anchor node moves to a new location based on spatial crowdsourcing. Then the distribution of the anchor nodes approximates to the location relationship shown in Fig. 3. At this time, the localization error is reduced to 0.82 m. In practical, the possible area where the unknown nodes are deployed can be known, with which anchor nodes can move to better locations for localization.

4.3 Node Upgradation

Because upgrading unknown nodes to be anchor nodes can improve localization performance, we first deploy 3 original anchor nodes and move the original anchor nodes to better locations for localization, then we upgrade an unknown node to be a new anchor node one time. As mentioned before, we select the unknown node with minimum localization error for simplicity and then upgrade the node.

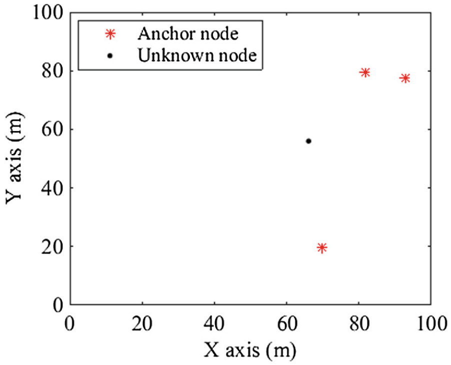

Fig. 6. Initial distribution of three anchor nodes.

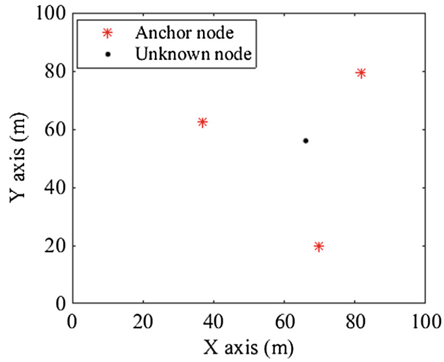

Fig. 7. Node distribution after node movement based on spatial crowd-sourcing.

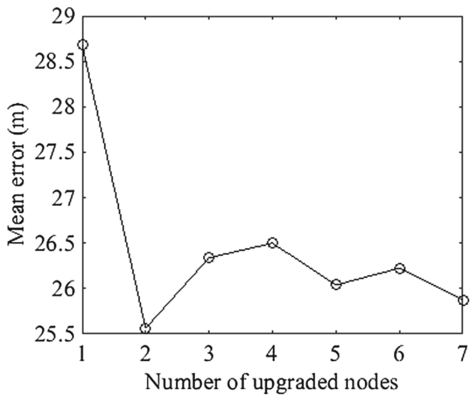

Fig. 8. Mean errors with different numbers of upgraded nodes.

Finally, localization coordinates are computed with DV-Hop method. In this paper, a total of 7 nodes are upgraded in turn and the mean errors with different numbers of upgraded anchor nodes are shown in Fig. 8.

In this paper, a total of 7 unknown nodes are upgraded to be anchor nodes. With the growth of anchor node number, the mean error first decreases sharply and reaches the minimum error. Then the mean error fluctuates, but it has a downward trend. As shown in Fig. 8, with three original anchor nodes, the minimum mean error is achieved when two unknown nodes are upgraded. The fluctuation is probably caused by random distribution of nodes. The mean errors with different numbers of anchor nodes are shown in Table 1. The simulation results show that our proposed method has a better localization performance with 10 anchor nodes than basic DV-Hop method whose mean error is 34.51 m.

Table 1. Mean errors with different numbers of anchor nodes

Anchor node number	4	5	6	7	8	9	10
Mean error (m)	28.68	25.56	26.35	26.50	26.04	26.22	25.87

5 Conclusion

In this paper, we study maximum likelihood method, DV-Hop method and influence of anchor node locations on localization performance in detail and also investigate the application of spatial crowdsourcing in sensor node localization. Then we proposed a spatial crowdsourcing-based sensor node localization method in IoT. Based on spatial crowdsourcing, anchor nodes move to new locations according to node location relationship for localization performance improvement. Then unknown nodes are upgraded as new anchor nodes and localization coordinates are computed by DV-Hop method. Simulation results show that our proposed localization method is able to achieve a better localization performance.

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