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3DT-PP: localization and path planning of mobile anchors over complex 3D terrains①

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Abstract

Mobile anchors are widely used for localization in WSNs. However, special properties over 3D terrains limit the implementation of them. In this paper, a novel 3D localization algorithm is proposed, called 3DT-PP, which utilizes path planning of mobile anchors over complex 3D terrains, and simulations based upon the model of mountain surface network are conducted. The simulation results show that the algorithm decreases the position error by about 91%, 8.7% and lowers calculation overhead by about 75%, 1.3%, than the typical state-of-the-art localization algorithm (i.e., 'MDS-MAP', 'Landscape-3D'). Thus, our algorithm is more potential in practical WSNs which are the characteristic of limited energy and 3D deployment.

Key words: concave/convex decomposition, path planning for mobile anchor nodes, 3D-localization algorithm, wireless sensor network (WSN)

0 Introduction

Wireless sensor network (WSN) is a wireless communication computer network constructed by a large number of sensor nodes[1]. It is widely used in the environment detection[2,3], military reconnaissance[4], family control[5], etc. Localization in WSNs is one of the main topics for researchers in this area. The existing localization strategies which mainly focus on 2D environment have been well studied. Actually, the more practical scenario is that the sensor nodes are deployed in the random 3D environment, such as mountain surface, underwater, space, etc. Therefore, it is necessary for us to improve the existing work to adapt to 3D terrains and to design a localization algorithm that has higher precision, lower energy consumption and smaller overhead.

With the development and application of the wireless sensor networks, the research on the sensor node localization and other basic technology are becoming more and more popular. To realize the complex 3D environment position, we do not only need to consider the positioning accuracy, positioning efficiency and energy consumption and so on, but also need comprehensive terrain, environment and other factors. In this way, some well studied 2D plane localization algorithms could be applied to complex 3D environment skillfully and make the applications of wireless sensor network used widely.

An anchor is a special GPS-equipped node in WSNs that can offer its absolute position, with high production cost and low energy consumption. However, anchor nodes are not suitable for large-scale deployment. One more economic method is to use more mobile anchor nodes, which can move to target area according to a specific trajectory in the region of interest (ROI), periodically broadcast their position and assist other nodes to calculate their own position. By this method, the cost of WSNs is reduced, the overwhelming overhead of computation caused by too many anchor nodes can be avoided as well. Therefore, how to dig out an optimal path and to divide the mountain surface network into sub-regions has become the key problem and needs solving[6].

Based on the observations above, we propose a novel localization algorithm, named 3DT-PP, which utilizes path planning of mobile anchors over complex 3D terrains. The contributions of our work are described as follows:

(1) A smart dividing strategy is proposed. In this strategy, the complex 3D terrains can be easily split into several relatively flat sub regions. As a result, the mobile anchor can move freely and the nodes can be

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easily measured;

(2) A local optimal solution of the ant colony algorithm is presented. This solution can be achieved by planning a reasonable path for the mobile anchors path in a sub-region. Therefore, the signal of a mobile anchor could cover the entire ROI as much as possible and reduce the repeat visit of the nodes;

(3) A reasonable scheme of path planning is designed. In this scheme, it offers a best path among the sub-regions that connects these sub-regions effectively. Therefore, the mobile anchors in different sub-regions can be connected more easily, and get the global optimal solution to locate more nodes, resulting in reducing the path length of the anchor nodes and the energy consumption of the common nodes;

(4) Through 3DT-PP, the calculation cost and energy consumption can be reduced significantly which is 77% lower than that of MDS-MAP', and 7.6% lower than that of 'Landscape-3D', since the complicated calculation is transferred from common nodes to mobile anchors.

1 Related work

To acquire the positions of anchor nodes, they usually need to be artificially deployed and installed with a GPS device. As a result, the costs of anchor nodes are higher than common ones. On the other hand, the scalability of static anchor nodes is worse than a mobile anchor node in terms of localization. Therefore, using mobile nodes instead of static anchor nodes for location is a feasible scheme.

The mobile anchor nodes periodically broadcast their position information to unknown nodes; one of which determines its own location based on this information. This method is similar to the static network localization algorithms[7], such as PHDV-Hop (mobile beacon DV-Hop)[8], virtual rule[9], ADO (arrival and departure overlap)[10], grid-based[11], etc. During the process of the anchor node movement, we can determine some straight lines which cross an unknown node, so the intersect point of the straight lines is the estimated location of the unknown node[12], such as LSWD (localization scheme for wireless sensor networks using directional antenna)[13], PI (perpendicular intersection)[14], etc. If the mobile anchor node is equipped with directional antenna or broadcasts packets with different powers[15], the localization results will be more accurate. In order to avoid the collinear problem caused by using a single mobile anchor node, we proposed a co-localization algorithm that uses multiple mobile anchor nodes in Ref. [16].

Acquiring the optimal path of the mobile anchor node is the basic requirement of high-performance localization. The optimal path should follow these requirements[17-20]: ① The mobile anchor node should pass as more unknown nodes as possible; ② Each unknown node should obtain enough information of the mobile anchor node; ③ To reduce energy consumption, the path should be as short as possible except the random mobile path. Some researchers also have proposed many algorithms, such as Scan[17], Double-Scan[17], Hilbert[17], Circles[19], S-Curves[19], and the methods that use graph theory or optimal overlap category to acquire the optimal path[17,18]. The dynamic path planning could be achieved by using the feedback information of unknown nodes and the directional antenna[21].

A novel flying landmark localization algorithm is proposed in Ref. [22], in which each landmark is equipped with a GPS receiver and broadcasts its location information as it flies through the sensing space. Then each unknown node in the sensing space estimates its own location based on the basic geometry principles and the received position information packets from the flying landmark. Simulation results show that when the transmission radius is 15m, the localization error of the algorithm is 1.6m, whereas the localization error of the centroid algorithm is 2.4m. But this method usually requires more hardware and the path is fixed as well. The advantage of this method is not obvious any more when the scalability of network increases.

MDS-MAP[23] uses MDS (multidimensional measurement), which can be regarded as a set of data processing technologies to show the geographical characteristics by using distance measurement. A major advantage is that it can obtain relatively higher position information, although it works based on the limited or even wrong distance information. Next, the position information of each node can be obtained based on the matrix transformation. But when the number of the nodes increases, the calculation of the algorithm trends to be complex and the requirement of memory space also increases quickly. The time complexity that the matrix is decomposed into orthogonal matrix and diagonal matrix is up to $o(n\hat{}3)$, therefore the energy consumption is considerably high.

Therefore, path planning is an important evaluation criterion in localization by using mobile anchors in the WSNs. However, the existing localization algorithms mainly focus on improving the performance in terms of accuracy. How to balance the optimal path (representing the minimum overhead of computation) and the accuracy of localization is an open problem in

WSN research filed. Besides, at present, the proposed algorithms about path planning are assumed to be suitable to plane (i. e., 2D space) where there are no obstacles. In this case, these kinds of models are lack of path planning in complicated scene. In this paper, we propose a path planning scheme using mobile anchor nodes to solve the problem of localization over 3D terrains, in which we divide the complex 3D environment into several relatively plain planes, resulting in a local optimal solution of sub-regions. They are connected into the global optimal solution.

2 Localization and path planning of mobile anchors over complex 3D terrains

2.1 Network initialization

In order to complete the anchor node path planning, we first need to know the structure of the network and relative information nodes, and then construct the weighted undirected graph of the entire network, and the weights of the graph are the distance between two nodes.

2.2 The definition of special nodes and division of sub-region

After the weighted undirected graph is obtained, the whole network can be divided (the original uneven terrain surface) into several flat sub-regions according to the defined special nodes

(1) The definition of concave/convex node

To decompose the nodes deployed in a 3D surface, the border nodes should be determined first. Herein the border nodes are defined as the ones which lie in a layer border. These border nodes are used to establish sub-areas. A node is considered as the lowest bound one if it is in the lowest of given sub-area. Similarly, a node is considered as an upper bound one when it lies in the upper of sub-areas. Let $S_k(p)$ denote the set of the nodes at the most k hops away to node p. $ES_k(p)$ is defined as the *k-hop* neighborhood of p, which contains that the nodes are exactly k hops away from node p. Clearly, $ES_k(p)$ can be regarded as a (or a part of) sphere centered at node p. Given any two nodes p_1, $q_1 \in ES_k(p)$, we define a perimeter from p_1 to q_1, denoted by $D_K^P(p_1, q_1)$, as the set of nodes which are on the shortest path from p_1 to q_1 using the nodes in $ES_k(p)$. Therefore we define the perimeter distance (i. e. the sum of hops), $|D_K^P(p_1, q_1)|$ from p_1 to q_1, as the number of sensors in $D_K^P(p_1, q_1)$ minus one, Define t as the number of nodes of $ES_k(p)$ set. To decrease the error of $C_k^t(p)$, we must get the max value of $|D_K^P(p_1, q_1)|$ n t nodes.

The definitions are exemplified by the example shown in Fig. 1, and the concavity/convexity is defined by:

$$C_k^t(p) = \frac{\rho}{2\pi k} \cdot \left(\max_{i \in \{1,2,\cdots,t\}} |D_k^p(p_1, q_1)| + 1\right), \quad (1)$$

where $\rho > 0$ is the scale factor for Euclidean distance and hops of the sensor nodes.

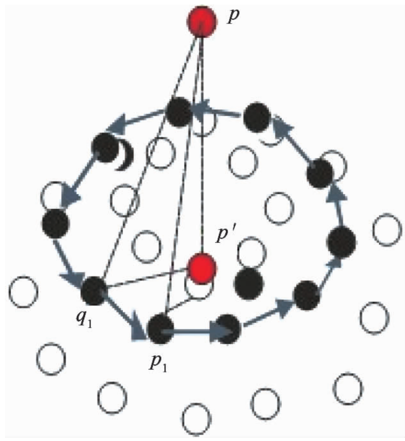

Fig. 1 The samples of concave node

If the surface on which nodes are deployed is close to plane, and these nodes are uniformly distributed, then $C_k^t(p) \approx 1$. Given a threshold θ, where $\theta > 0$, a node is considered as concave/convex if $C_k^t(p) < 1 - \theta$. Note that threshold θ can be obtained on the basis rule of thumb.

Under the assumption that $k \leqslant 3$, the sub-region of 3D surface is prone to be smooth in the given area. So the path shaped by the nodes in $ES_K(t)$ approximately forms a circle. As a result, it can be measured by a perimeter.

As Fig. 1 shown, a node p, Let $k = 2, t = 1$, p_1 and q_1 be the starting node and the ending node, respectively, and according to Eq. (1)

$D_2^P | p_1, q_1 | = 9$. Correspondingly, $\frac{(D_2^P | p_1, q_1 | + 1)}{2 \times 2\pi} = \frac{(9+1)}{12.56 = 0.79 < 1 - 0.20}$, where $\theta = 0.20$, and $\rho = 1$ for simplicity.

(2) Region segmentation

By the above method, we get the concave/convex nodes and a rough outline structure of the concave/convex nodes, and then obtain planes roughly. We find the convex nodes and connect them and make specialization of the original link from the concave/convex node. Therefore, the entire network can be divided into a plurality of sub areas, and each sub area can is be constructed an approximate plane structure.

The region segmentation algorithm flowchart is shown in Fig. 2.

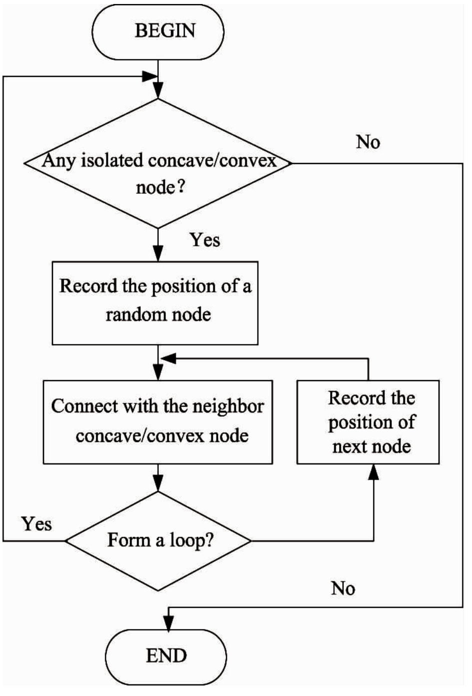

Fig. 2 Region segmentation algorithm flowchart

After segmentation of the sub-region, we check the connectivity between the areas and abstract each sub region as a node. If there are two or more lines on the topological structure of the network, we connect the sub-region in the sub-region graph. In order to accomplish the sub-network connection, it is necessary to find out the Hamilton passage, and then seek a path through all the nodes, and the passage passes through each node only once. As a reuslt, the total shortest distance (or the total minimum weight) of the entire path can be obtained.

2.3 Path planning for mobile anchor nodes

Based on the work described above, the basic network topology and connection properties can be got. In this section, a new scheme will be presented which offers an effective and complete path planning of mobile anchor nodes using the network topology and connection properties. Our planning scheme can shorten the moving path of the mobile anchor node, complete the 3D terrain surface sensor for precise localization and reduce the calculation cost of the sensor nodes.

(1) Path selection

Based on the previous work discussed above, the sub-region set can be obtained roughly. Assume that each sub-region is plane and the path planning in each of them can be constructed, respectively.

Given mobile anchor localization radius R (the semi diameters of the 4 nearest RSSI), $V = \{v_1, v_2, \cdots, v_n \in S_K\}$, S_k is the sub-region to be localized, v_n is the vertex on S_k. Inner vertices of v_1 are the nodes in the circle centered at vertex v_1 with the radius of R.

When localization begins, vertex v_1, is selected first randomly, then inner vertex v_2 is chosen, and all the inner vertexes in V subtract v_1. The construction process continues until there is no vertex in V. Thus we can make sure that each node can get its information and a useful path.

However, the path is not optimal since v_2 is selected randomly. To obtain a better path, we utilize the ANT algorithm[22] to complete this job. Table 1 shows the terms and meanings of the proposed algorithm.

Table 1 Symbols and their meanings in ANT algorithm

Signals	Meanings
N	Nodes number
C	Nodes Set
$d_{ij}(i, j = 1, 2, \cdots, N)$	Distance between i and j
D	Distance set (ranged by RSSI)
$b_i(t)(i = 1, 2, \cdots, N)$	Ant number at time t, node i
$M = \sum_{i=1}^{N} b_i(t)$	Ant number
$h_i(i = 1, 2, \cdots, N)$	Hops for node i to current node
$c_i(i = 1, 2, \cdots, N)$ $(c_i >= 1)$	Adjacency list size of node i
$\tau_{ij}(t)$, $(\tau_{ij}(0) = constA)$	Pheromone density at time t on the edge of i and j
τ_{ij}^{α}	Accumulate pheromone density on the edge of i and j
α	Effect on path select of pheromone density
η_{ij}^{β}	Exceptions on choosing edge i, j under inspiring factor's influences
β	Effect on path select of path length
φ_{ij}^{γ}	Exceptions on choosing the next vertex as j on node i under inspiring factor's influences of neighbor nodes number
γ	Effect on path select of neighbor nodes number
ψ_{ij}^{δ}	Exceptions on choosing the next vertex as j on node i under inspiring factor's influences of hop number
δ	Effect on path select of hop number

where $\eta_{ij}(t) = 1/d_{ij}, \phi_{ij}(t) = 1/c_j$ (the nodes which have the smallest number of neighbor nodes should be visited in the order of priority since there is a lower probability for these nodes to become neighbors next time), $\psi_{ij}(t) = \frac{1}{h_j}$ (the nearest neighbor should be visited first. When all the neighbors have been visited, unvisited nodes are looked for in a reverse direction).

Let $p_{ij}^{k}(t)$ be the probability for $k(k = 1,2,\cdots, M)$ ants which move from node i to node j at time t, the one step transition probability $p(t)$ can be given by

$$p(t) = \begin{cases} \dfrac{\tau_{ij}^{\alpha} \times \eta_{ij}^{\beta}(t) \times \varphi_{ij}^{\gamma}(t) \times \psi_{ij}^{\delta}(t)}{\sum\limits_{j=\text{allowed}_k} \tau_{ij}^{\alpha}\eta_{ij}^{\beta}(t)\varphi_{ij}^{\gamma}(t)\psi_{ij}^{\delta}(t)} & j \in \text{allowed}_k \\ 0 & \text{others} \end{cases} \tag{2}$$

where $\text{allowed}_k = \{N - tabu_k\}$ represents the node that ant k is allowed to move, $tabu_k$ denotes the forbidden table of $k(k = 1,2,\cdots,M)$ ant. This table is used to restore all the nodes that ants have passed.

Positive information feedback: in each iteration, an ant must update the pheromone of the path when it finishes its routine. The information can be regarded as the reference of the following ants. Assume the time duration is s, the pheromone is updated as

$$\tau_{ij}(t + s) = (1 - \rho)\tau_{ij}(t) + \Delta\tau_{ij} \tag{3}$$

$$\Delta\tau_{ij} = \sum_{k=1}^{M} \Delta\tau_{ij}^{k} \tag{4}$$

where ρ means the volatilized action of pheromone, $1 - \rho$ shows the remain pheromone factor accordingly, $\rho \in [0, 1]$, $\Delta\tau_{ij}$ means the pheromone increment of the iterate from node i to j. $\Delta\tau_{ij}(0) = 0$. And $\Delta\tau_{ij}^{k}$ means the pheromone left by the k^{th} ant on path (i, j) in the current iteration. The ant-density model is used to calculate $\Delta\tau_{ij}$:

$$\Delta\tau_{ij}^{k}(t) = \begin{cases} Q & \text{if the } k \text{ th ant goes through } (i, j) \text{ at time } t + 1 \\ 0 & \text{Otherwise} \end{cases} \tag{5}$$

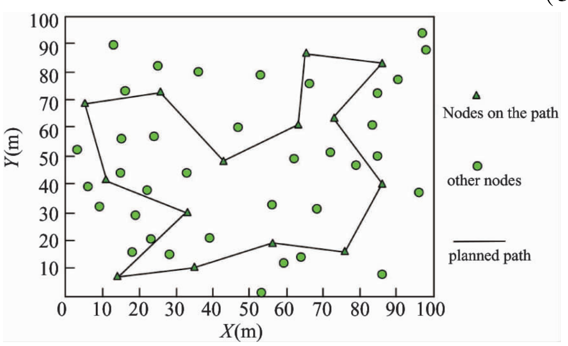

Fig. 3 Path planning based on the finally formed circle. 100m × 100m plane region

After a path that can localize all nodes is got the beginning and the ending nodes are connected to form a circle as Fig. 3 shown.

(2) Path planning within planes

The Hamilton path is used to plan after finishing localization in each sun-region, and two sub-regions are connected in the topology graph of the sensor network while two shortest paths are used according to the position in Hamilton graph. Then the cross vertex is disconnected within the sub-area to form a larger loop and cover more areas, then the above processes are done continuously, until the path covers the whole Hamilton graph, where the process is shown in Fig. 4. The pseudo-code of the proposed algorithm is shown in Algorithm 1:

Algorithm 1: Acquiring a lager path through Hamiltonian graph

input: assume network node topology $G_w = (V_W, E_W)$,
Sub-Regional simplified topology $G_S = (V_S, E_S)$
output: modified network node topology $G_w = (V_W, E_W)$,
While $E_S \neq \varnothing$ /* visit and connect each Sub - Region */
If $E_{s_n} = < V_{s_n}, V_{s_{n+1}} >$ *Exsits*
$\exists E_{WS_{n1}} = < V_{W_1S_n}, V_{W_1S_{n+1}} >, E_{WS_{n2}} = < V_{W_2S_n}, V_{W_2S_{n+1}} >$;
$G_w -= < V_{w_1S_n}, V_{w_2S_n} > - < V_{w_1s_{n+1}}, V_{w_2s_{n+1}} > + E_{ws_{n1}} + E_{ws_{n2}}$;
/* connect two Sub-Regions */
$E_S -= E_{S_n}$ /* delete the corresponding edge in the Hamiltonian graph */
End if
n ++; /* next Sub -Region */
End while

2.4 Localization by mobile anchor nodes

With the above process, a feasible anchor node moving path is got. After that all nodes on the planned path are informed. The mobile anchor node will start to search for all kinds of these nodes after above process. The mobile anchor node should be equipped at least four RSSI transmitters on different planes. The mobile anchor node will track the sensor node along the path. Within the process, mobile anchor nodes can use GPS or other methods to find their position. When the mobile anchor meets a node on the path, it calculates its position and sends the results to the node and its inner nodes. After that, the node does not conduct the calculation related position. Throughout the whole process, the mobile anchor node tracks down a path to the destination node continuously, and the target node transmits signals at the same time. After localization, the target node will turn off its signal transmitting immediately, and the next node on the path will start to transmit signals, which continues until the localization finishes. The process is shown in Fig. 5.

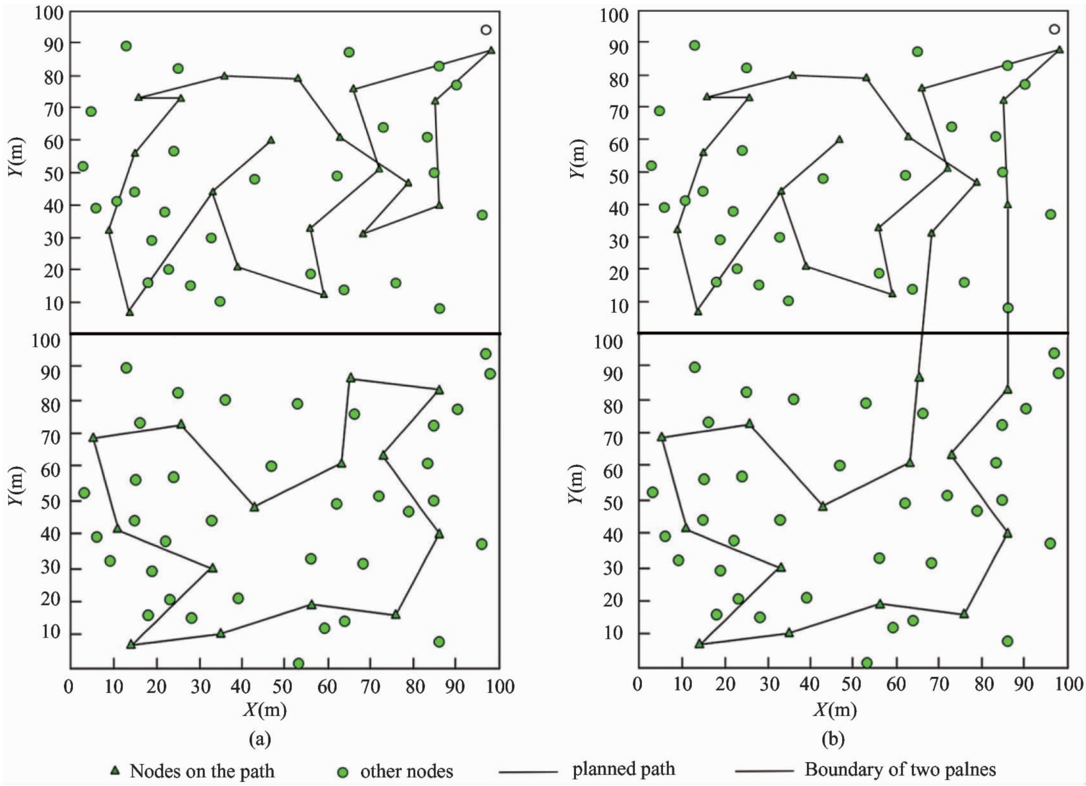

Fig. 4 Connection of two sub-regions. The bold line is the boundary. (a) is original network. (b) forms a larger circle to connect two sub-regions and connect every sub-region to form a circle of the whole network.

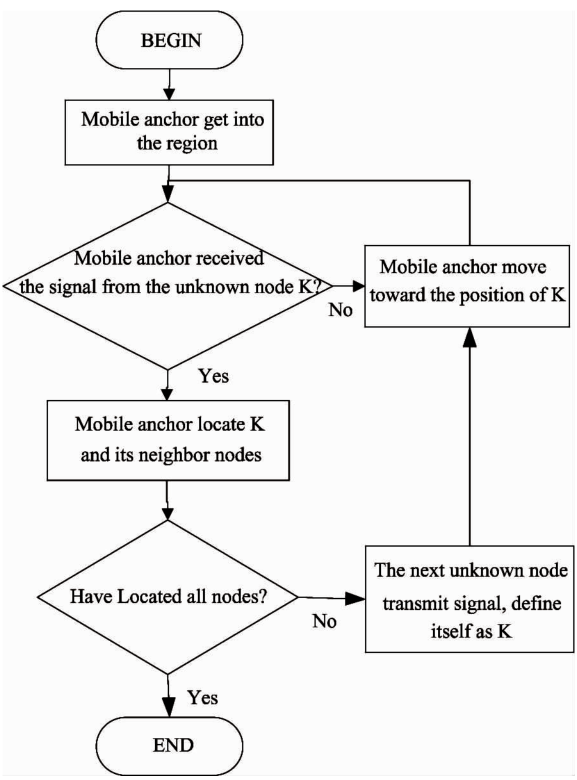

Fig. 5 Localization by mobile anchor node

3 The experiment and simulation results

In order to validate the reliability and performance of the mobile anchor node path planning algorithm, which has been discussed in Section 2, in the proposed experiments, the complex 3D terrain model of 3D-TTP in Matlab 7.0 is simulated. It is assmued that the nodes of the terrains are deployed randomly and uniformly. The advantages of our algorithm are more obvious when the number of nodes increases. Therefore an appropriate large number of nodes are selected for this simulation. In the proposed experiment, all the parameters which need to be given values have been put forward in the algorithm. The parameter value will not be changed except some special instructions are needed. We compare the performance of 3D-PPT with Landscape-3D[23] and MDS-MAP[24].

Simulation experiment will be made in this section. The experiment consists of two parts. In part 1, the reliability of the algorithm is validated and the shortest path length is calculated with different amount of nodes to check whether the algorithm could reduce the move length of the anchor node when the signal covers the whole LOI. In part 2, the algorithm is compared with other algorithms, and the advantages/disadvantages of the algorithm are analyzed comprehensively.

3.1 The global optimal solution found by the path planning algorithm with different number of nodes

The parameters of the ant colony algorithm are: path loss coefficient $\lambda = 2$, pheromone volatile coefficient $\rho = 7$, pheromone weight $\alpha = 3$, stimulating factor weight $\beta = 4, \gamma = 2, \sigma = 1$, pheromone incremental $\Delta\tau_{ij} = 0.02$, and the ant number $M = 1000$.

Assume that the initialized number of nodes is N, and in this section we will simulate these systems with 50, 100, 200, 400, 800 nodes, respectively corresponding to the total number of 500, 1000, 2000, 4000, 8000 sensor nodes. These nodes are randomly deployed in three-dimensional space of 100m × 100m × 100m, and the mobile anchor traverses all initialized nodes by traversal path planning based on the 3DT-PP algorithm as Table 2 shown.

Table 2 Best path length

Initialize nodes number (to be localized)	Best Path Length (m)
50	200m
100	512m
200	1000m
400	2000m
800	3900m

The experimental results show that the planned path of the 3DT-PP algorithm can be achieved for different number of nodes to be traversed, which has more advantages in a large complex concave/convex network. As the number of nodes grows, path length does not show any unusual increase, but rather a smooth uniform growth. This proved that our algorithm has good stability and reliability.

3.2 The comparison between different algorithms

To get the comprehensive performance of the proposed algorithm, we compare the algorithm with MDS-MAP(P, R) and Landscape-3D with '3DT-PP' and then obtain the accuracy of measurement and energy consumption of different algorithms under the same outside environment.

Distance measurements are assumed to have Gaussian noise[25]. Stochastic noise is added to the true distance as

$$\hat{d} = d \times (1 + randn(1) \times rang\_error) \qquad (6)$$

where d is the true distance, $\hat{d}$ is the measured distance, $rang\_error$ is a value between [0, 1], and $randn(1)$ is a standard normal random variable.

(1) The influence of the anchor node density

The localization accuracy of 3DT-PP algorithm increases as the anchor node density increases. When the ratio of anchor nodes is above 15%, localization accuracy is better than the other two algorithms and the higher the anchor node density, the more obvious this advantage shown in Fig. 6.

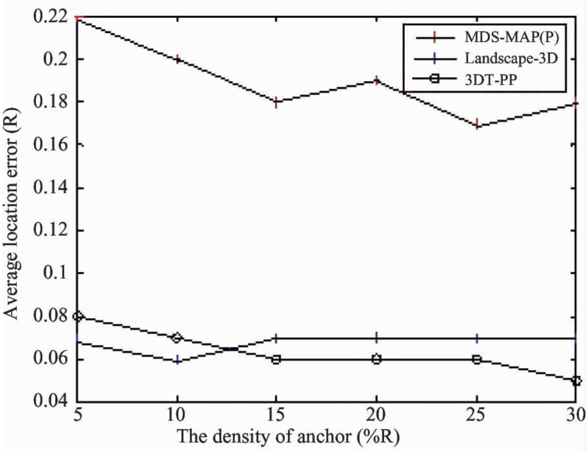

Fig. 6 The influence of the anchor node density

Fig. 6 shows the computation cost is linearly proportional to the number of beacons used, which provides great flexibility to sensor nodes: when the energy is low, the sensor nodes can intentionally drop some beacons to save the power.

(2) The RSSI error influence of average localization error

In this subsection, we compare the average error rate of our algorithm (i. e., '3DT-PP') with 'Landscape-3D' and 'MDS-MAP'. Simulations show that, to obtain the same level performance, '3DT-PP' algorithm has a lower distance measurement error and average location error, and has a higher positioning accuracy, compared to 'Landscape-3D' and 'MDS-MAP' in terms of position precision, as shown in Fig. 7. Although the position precision of '3DT-PP' and 'Landscape-3D' and 'MDS-MAP' decreases as the distance measurement error increases, obviously, the average position error of '3DT-PP' is lower than that of 'Landscape-3D' and 'MDS-MAP'. Under the scenario in which RSSI error rate is 30%, the average localization error of our algorithm (i. e., '3DT-PP') is 27% lower than that of 'MDS-MAP', and lower than that of 'Landscape-3D'. When RSSI errors is still at 25%, the average localization error of '3DT-PP' is 36% lower than that of and 'MDS-MAP', and 18% lower than that of 'Landscape-3D'. When RSSI error is still at 20%, the average localization error of '3DT-PP' is 55% lower than that of 'MDS-MAP', and 30% lower than that of 'Landscape-3D'. At the same time, the average position error has nothing to do with the scale of the network, and the average positioning error of 3DT-PP is less than the other alogirithms, which can ensure that 3DT-PP achieves a high positioning accuracy.

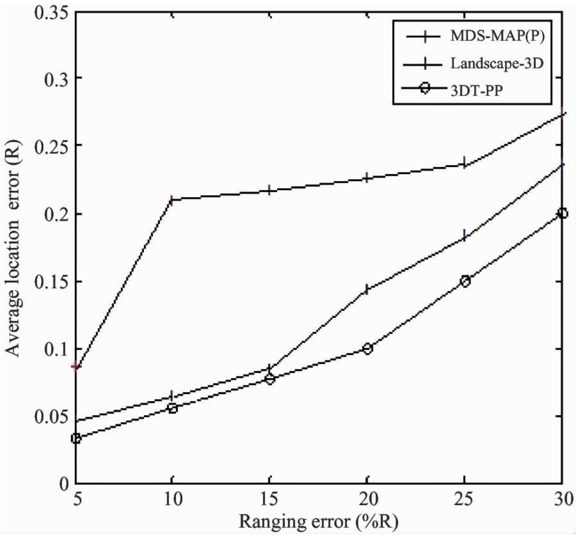

Fig. 7 The influence of the RSSI error

(3) The comparison between average position error and CPU time consuming the different algorithms

In this subsection, the accuracy (position error) and computation overhead of our algorithm are (i. e., '3DT-PP') compared with 'Landscape-3D' and 'MDS-MAP'. For comparison, we report the CPU time consumed (per sensor node) by position algorithms in our simulations. All simulations are conducted on a DELL precision 670 workstation (Intel Xeon 3.0 GHz CPU, DDR-2, 2 GB memory).

For the simulation of MDS-MAP, MDS-MAP (P, R) is used, which is the distributed version of MDS-MAP with a refinement procedure. The performance of MDS-MAP algorithm depends on the network connectivity. Generally, the higher the connectivity, the higher the accuracy and computation cost. In simulations, the connectivity could be changed by varying the sensor's radio range (Since sensor nodes are randomly deployed, even with the same sensor radio range, the connectivity could be slightly different in different trials.). In the experiments for MDS-MAP (P, R), 5% nodes are assumed as anchor nodes (with known locations).

More details of the comparison are given in Table 3. To eliminate the effect of occasionality, the average of another 1000 trails (sensors are randomly re-deployed for each trail) is also reported in the table. 3DT-PP yields much higher accuracy with less computation overhead. Experiments show that '3DT-PP' algorithm is much lower in terms of position error and calculation overhead compared to 'Landscape-3D' and 'MDS-MAP', When the parameters and the average of 1000 trails keep unchanged, the position error of our algorithm (i. e., '3DT-PP') is 91% lower than that of 'MDS-MAP', and 8.7% lower than that of 'Landscape-3D'. The CPU time per node of our algorithm (i. e., '3DT-PP') is 75% lower than that of 'MDS-MAP', and 1.3% lower than that of 'Landscape-3D'.

Table 3 Comparison of 3DT-PP with other existing algorithms in a flat terrain with irregular topology

		Parameter			Results	
	Algorithms	Sensor Radio Range	Connectivity	Range Error	Position error	CPU time per node
One trail	MDS-MAP(P,R)	200	25.712	10%	106.764	0.544sec
	Landscape-3D	N/A	N/A	10%	11.216	0.143sec
	3DT-PP	N/A	N/A	10%	10.116	0.140sec
Another trail	MDS-MAP(P,R)	250	33.130	10%	58.097	1.249sec
	Landscape-3D	N/A	N/A	10%	11.712	0.141sec
	3DT-PP	N/A	N/A	10%	10.128	0.139sec
Average of another 1000 trails	MDS-MAP(P,R)	200	26.016	10%	115.357	0.568sec
	Landscape-3D	N/A	N/A	10%	11.092	0.143sec
	3DT-PP	N/A	N/A	10%	10.119	0.141sec

Table 3 shows the comparison of 3DT-PP and other algorithm in a flat terrain with irregular topology using integrated above experimental data; 3DT-PP yields a much higher accuracy with less computation overhead. We find that the localization error and CPU cost of 3DT-PP algorithm are lower than MDS-MAP (P, R) and Landscape-3D.

4 Conclusions

In this paper, a robust sensor localization alogrithm is proposed, called 3DT-PP. Besides several advantages over the existing sensor positioning approaches, such as high accuracy, high scalability and low computation cost and communication cost. Besides, 3DT-PP also provides the optimal path for the mobile anchor nodes, and these nodes in 3DT-PP can be transferred according to the path and be positioned precisely on the entire mountain surface. The simulation results show that 3DT-PP is an effective location-finding approach for sensor networks deployed over complex 3D terrains.

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