Accurate Range-free Localization Based on Quantum Particle Swarm Optimization in Heterogeneous Wireless Sensor Networks

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Abstract

This paper presents a novel range-free localization algorithm based on quantum particle swarm optimization. The proposed algorithm is capable of estimating the distance between two non-neighboring sensors for multi-hop heterogeneous wireless sensor networks where all nodes' communication ranges are different. Firstly, we construct a new cumulative distribution function of expected hop progress for sensor nodes with different transmission capability. Then, the distance between any two nodes can be computed accurately and effectively by deriving the mathematical expectation of cumulative distribution function. Finally, quantum particle swarm optimization algorithm is used to improve the positioning accuracy. Simulation results show that the proposed algorithm is superior in the localization accuracy and efficiency when used in random and uniform placement of nodes for heterogeneous wireless sensor networks.

Keywords: Heterogeneous wireless sensor networks, range-free localization, multi-hop, expected hop progress, quantum particle swarm optimization

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1. Introduction

Recently, wireless sensor networks (WSNs) have attracted keen attentions in various applications such as monitoring a spatial physical phenomenon and tracking mobile targets [1-4]. It comprises of many sensors randomly/spatially distributed over a certain area with the purpose of extracting, processing and transmitting information in the monitoring area [5-6]. In WSNs, node localization is the key technology and the detection of message without location information is meaningless.

Nowadays, the research of localization algorithms is mainly focused on homogeneous wireless sensor networks and little on heterogeneous wireless sensor networks (HWSN). However, heterogeneity problem of WSNs exists commonly because of the differences in node energy, computing power, network protocol and communication link, etc. The heterogeneity may affect barrier coverage, the localization method, localization mechanism and the maximum communication radius between nodes. For HWSN, several researchers have done some research on barrier coverage problems [7-9]. However, there is little research about different communication radius of sensor nodes. Obviously, sensor nodes with different communication radius severely reduce connectivity of networks, thereby increase distance calculation error, which ultimately lead to low positioning accuracy. Therefore, in this paper we study the optimization method of node location for HWSN where all nodes' communication ranges are different.

Traditional range-free algorithms, which assume the same communication capability throughout the network, make the localization accuracy poor in HWSN. Thus, several researchers have proposed expected hop progress (EHP) approach to estimate the distance between anchor nodes (ANs) and unknown nodes (UNs) for HWSN [10]. The algorithm depends not only on the communication radius of ANs, but also on the communication radius of inter-nodes (INs), which are closer to a real Euclidean distance between any two nodes. The problem with the approach, however, is that conditional cumulative distribution function (CDF) has a high computing complexity and the localization condition cannot be always guaranteed, especially when the node communication radius are not small enough. To solve these problems, a modified EHP approach is presented by redefining a new CDF and achieves satisfactory localization results [11]. However, the main drawback is that the modified approach has additional overhead and energy consumption because of training before redefining CDF. On the other hand, basic methods of calculating sensor nodes' location (i.e., Trilateration, Triangulation and Maximum Likelihood Estimation (MLE)) are not appropriate for HWSN where any distance estimation error can have a significantly different impact on localization accuracy. For instance, errors are expected to occur when estimating the distance between nodes and computing the coordinates of UNs by MLE, thereby hindering localization accuracy. To improve localization accuracy error of traditional position calculation methods, many researchers proposed different optimization approaches, such as genetic algorithm (GA) [12], particle swarm optimization (PSO) [13] and quantum particle swarm optimization (QPSO) [14]. QPSO has the advantage of fast convergence, and it can play a quick and easy solution advantage of intelligent optimization algorithms. Therefore, QPSO algorithm is more applicable to multi-hop HWSN localization. But, most of localization optimization algorithms are aim at homogeneous wireless sensor networks with the same communication radius, which is less used in the study of HWSN localization.

Up to now, no method can obtain the satisfying localization results for HWSN. In this paper, to optimize the positioning algorithm, we propose a novel localization algorithm based on EHP and QPSO in the realm of multi-hop range-free localization schemes. Firstly, we assume that transmission coverage of each node is circular, i.e., the degree of irregularity (DoI) of the communication radius is equal to zero. Then, a new CDF expression of EHP is constructed to reduce the computational complexity. And the mathematical expectation of CDF is considered estimation distance. Finally, QPSO algorithm is used for localization optimization.

The remainder of this paper is organized as follows. In Section 2, we elaborate the localization model of multi-hop HWSN in the two-dimensional space, and introduce hop progress model for different communication range and node density. Section 3 describes the proposed range-free localization algorithm and analyzes QPSO algorithm in multi-hop HWSN. Experimental results analysis is given in Section 4 and concluding remarks are made in Section 5.

2. Network Model

In real life, most WSNs deployments are performed though low flying airplanes or unmanned ground vehicles. We assume that all sensors, deployed randomly and uniformly, are heterogeneous, omnidirectional and stationary. Meanwhile, consider a HWSN in a 2D square area $S=L\times L$ with N sensors, donated by a set $N = (n_1, n_2, \ldots, n_N)$, where n_i is the i-th sensor. ANs are marked with red asterisks to help in estimating sensors' positions, and UNs marked with red circles is to compute its location based on the information obtained from ANs, as shown in **Fig. 1**. The link between any two nodes represents one hop, which is able to reach or communicate with other sensors.

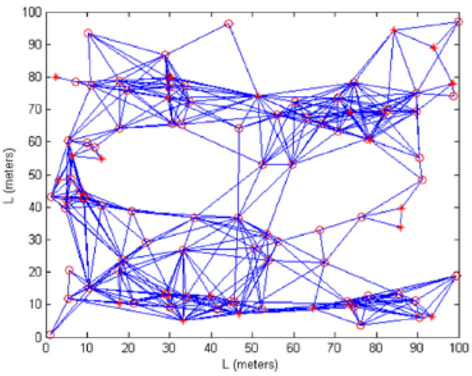


Fig. 1. Heterogeneous wireless sensor network model

In multi-hop HWSN localization, the goal is to estimate the location of all UNs by using ANs and partial information of the distances between some pair of ANs and UNs. For the sake of simplicity, we employ the shortest path method to obtain a possible path between a source sensor and a destination sensor with the minimum number of hops. Then using ANs' available information, j-th unknown node computes easily an estimate of its distance to the i-th anchor as $d_{i\text{-}j}\approx d_{i\text{-}k} + d_{k\text{-}j}$, where $d_{i\text{-}k}$ ($d_{k\text{-}j}$) denote the distance between ANs (INs) and INs (UNs). Compared with homogeneous localization algorithms, sensor nodes' per hop distance possesses huge discrepancy because of different maximum communication radius, as shown in **Fig. 2**. In homogeneous WSN, multi-hop range-free localization algorithms, to a certain extent, caused biggish distance estimation error due to that it exploits the same hop distance instead of inter-nodes each hop Euclidean distance. To solve this problem, accumulative distance is refined to calculate each hop distance by using the minimum mean square error (MMSE) of the distance estimation method as [10-11]

$$\hat{d}_{i-j} = E\left(d_{i-j}\right) \approx E\left(d_{i-k_1}\right) + E\left(d_{k_1-k_2}\right) + \ldots + E\left(d_{k_{m-1}-k_m}\right) + E\left(d_{k_m-j}\right) \tag{1}$$

where k_m denotes m-th inter-node. $E(d_{i\text{-}k_1})$, $E(d_{k_{m\text{-}1}\text{-}k_m})$ and $E(d_{k_m\text{-}j})$ represent first-hop distance, inter-node hop distance and the last-hop distance, respectively. Therefore, this is obvious that to obtain the estimate distance $\hat{d}_{i-j}$ between ANs and UNs, three distance formulae need to be derived, i.e., first-hop distance, inter-node hop distance, the last-hop distance, which are given in the next section respectively.

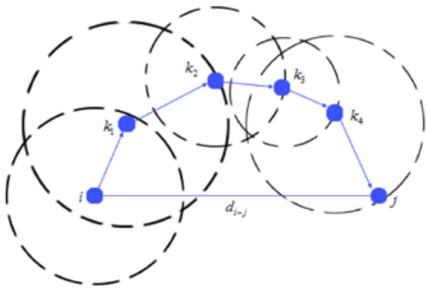


Fig. 2. Multi-hop communication

In the network model, we assume that UNs have the capacity to receive the information from ANs for distance estimation, then iteratively optimizing the coordinates of unknown node by QPSO. Meanwhile, transmission coverage area is considered to be circular. The major symbols used in this paper are listed in **Table 1**.

Table 1. The major symbols used in this paper

Symbols	**Definitions**
i, k, j	anchor nodes, inter-nodes and unknown nodes, respectively
r_i, r_k, r_j	communication radius at the i-th anchor node, the k-th inter-node and the j-th unknown node, respectively
N, N_a, N_u	the number of all nodes, anchor nodes and unknown nodes.
$area(i,r_i)$, $area(k,r_k)$	the i-th (k-th) node's coverage area having the i-th (k-th) sensor as a center and r_i as a circle of radius
$area(j,r_k)$	the j-th unknown node's coverage area having the j-th unknown sensor as a center and inter-node radius r_k as a circle of radius
λ	node density in monitoring area
θ, θ', θ_z and θ'_z	angle of the linkbetween anchor nodes and unknown nodes
$d^E_{i\text{-}k_1}$, $d^E_{k_{m\text{-}1}\text{-}k_m}$, $d^E_{k_m\text{-}j}$	first-hop distance, inter-node hop distance and the last-hop distance, respectively
(x_j,y_j)	the coordinates of unknown nodes
M	the size of swarm
t_{max}	the maximum number of iterations

3. Analytical evaluation of EHP and QPSO

In this section, expressions of hop distance are accurately derived aiming at sensor nodes with different maximum communication radius. Then, the localization optimization algorithm is studied in detail, in which we mainly introduce the principle of QPSO and analyze the convergence of criterion QPSO.

3.1 Hop Distance Derivation Using EHP Approach

For the sake of clarity, this paper is only to discuss the two-hop distance, in what follows, we denote by X, Y and Z the random variables that represent $d_{i\text{-}j}$, $d_{k\text{-}j}$ and $d_{i\text{-}k}$ respectively [10-11]. Then, the probabilistic distribution mode for multi-hop HWSN is developed using the conditional cumulative distribution function (CDF) $F_{Z|X}(z)=P(Z\leq z|x)$ of Z with respect to the random variable X.

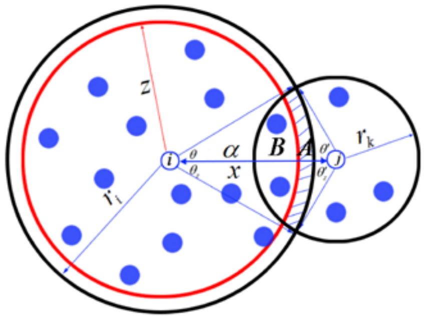


Fig. 3. EHP analysis

In **Fig. 3**, $Z\leq z$ is guaranteed only if there are no nodes in the dashed area A. Therefore, the conditional CDF can be defined as [10-11], [15]

$$F_{Z|X}(z)=P(Z\leq z\,|\,x)=P(A_0) \tag{2}$$

where $P(A_0)$ is the probability of the event A_0, A_0 indicates no nodes in the dashed area A. Let Q be the potential forwarding area wherein k-th node communicates directly with the j-th node. Meanwhile, i-th node can indirectly transmit information to j-th node through inter-node k in the area Q. Then, Q, which relies on both r_i and r_k, is given by

$$Q=area(i,r_i)\cap area(j,r_k)=A\cup B \tag{3}$$

And, the probability of K nodes in area A follows Binomial distribution X~$B(N, p)$ where $p=A/S$. For relatively large N and small p, $B(N, p)$ can be accurately approximated by a Poisson distribution. Enlightened by the reference 15, we employ simplified conditional CDF formulas, which can adapt to the heterogeneous nature of WSNs. Therefore, we have

$$F_{Z|X}(z)=e^{-\lambda A} \tag{4}$$

Where

$$\lambda = Np = \frac{N}{S} \tag{5}$$

By using some geometrical properties to find the geometric relation between the anchor node and the unknown node, and in accordance with trigonometric transformations and rules to represent this relation, so the area of the shaded part A can be given by

$$A = r_i^2\left(\theta - \frac{\sin(2\theta)}{2}\right) + r_k^2\left(\theta' - \theta_z' + \frac{\sin(2\theta_z') - \sin(2\theta')}{2}\right) - z^2\left(\theta_z - \frac{\sin(2\theta_z)}{2}\right) \tag{6}$$

where

$$\begin{cases} \theta = \arccos\left(\left(r_i^2 - r_k^2 + x^2\right)/\left(2r_i x\right)\right) \\ \theta' = \arccos\left(\left(r_k^2 - r_i^2 + x^2\right)/\left(2r_k x\right)\right) \\ \theta_z = \arccos\left(\left(z^2 - r_k^2 + x^2\right)/\left(2zx\right)\right) \\ \theta_z' = \arccos\left(\left(r_k^2 - z^2 + x^2\right)/\left(2r_k x\right)\right) \end{cases} \tag{7}$$

Combined with the above analysis, the EHP between i-th anchor node and k_1-th inter-node can be derived as follows [10], [11], [15]

$$\begin{aligned} d_{i-k_1}^E &= \int_{r_i}^{r_i+r_{k_1}} \left(\mu\left(1 - F_{Z|X}(\mu)\right) + \int_{\mu}^{r_i}\left(1 - F_{Z|X}(z)\right)dz\right) f_X(x)dx \\ &= \int_{r_i}^{r_i+r_{k_1}} \mu\left(1 - F_{Z|X}(\mu)\right) f_X(x)dx + \int_{r_i}^{r_i+r_{k_1}}\left(\int_{\mu}^{r_i}\left(1 - F_{Z|X}(z)\right)dz\right) f_X(x)dx \end{aligned} \tag{8}$$

where $\mu = x - r_{k_1}$, $f_X(x) = 1/r_{k_1}$ is the probability density function (pdf) of X. The distance computing model of inter-node hop distance $d_{k_{m-1}\text{-}k_m}^E$ is the same as first-hop distance $d_{i\text{-}k_1}^E$, and so it can be obtained by formula (8). However, by definition, equation (8) is inapplicable for calculating the last-hop distance.

Since the j-th unknown node could be located anywhere in $area(k,r_k)$ with the same probability, the last-hop $d_{k_m\text{-}j}^E$ is given by

$$d_{k_m-j}^E = \int_0^{r_{k_m}} y f_Y(y)dy = \int_0^{r_{k_m}} \frac{y}{r_{k_m}} dy = \frac{r_{k_m}}{2} \tag{9}$$

where Y is considered as a distributed random variable on $[0, r_{km}]$, $f_Y(y) = 1/r_{km}$ denotes pdf of Y. According to hop distance equations, EHP approach depends not only on the communication radius of ANs, but also on the communication radius of INs. Therefore, the so-obtained estimation distance is more accurate than traditional range-free localization algorithms in multi-hop HWSN.

By avoiding complex conditional CDF formulas exploited in reference 10 and reference 11, the obtained EHP in this paper is higher in efficiency, lower in energy consumption, and easy to calculate. In addition, the proposed method is more accurate for the situation of low network node density and low proportion of beacon nodes. Unfortunately, With the increase of sensor nodes density, positioning accuracy is not satisfactory comparing with the existed EHP method for HWSN. In order to resolve this problem, we have introduced QPSO in the next section.

3.2 Quantum Particle Swarm Optimization

In order to improve the accuracy and efficiency of multi-hop localization algorithm, many optimization algorithms are proposed such as particle swarm optimization (PSO) and quantum particle swarm optimization (QPSO). PSO simulates the swarm behavior of birds and transfers the process of seeking the best solution for specific problems to the process which particles scout the best position in a certain area [16-17]. The shortcoming of the optimization model is easily trapped in the local optimum and appeared premature convergence. QPSO, proposed and developed by Sun et al. [18], is a modification of the standard PSO algorithm in the domain of quantum computing. QPSO shows fast convergence performance and stronger global search capability.

In QPSO algorithm, since the velocity and position of each particle cannot be determined together, the quantum state of the particle is represented by a wave function $\phi(Y) = 1/\sqrt{L} * e^{-|Y|/L}$. By the Monte Carlo method, the equation representing the position of particle is given as

$$X = P \pm \frac{L}{2} \ln\left(\frac{1}{u}\right) \tag{10}$$

where X represents the particle position, P is the local attractor of particle and u is a random number in the range of [0,1]. $L=1/\beta$ is the probability that the particle will appear at the opposite point position, in which β is the shrinkage factor varying with time t. Thus, equation (10) can be written as [19]

$$x_i(t+1) = p_i(t) \pm \frac{L(t)}{2} \ln\left(\frac{1}{u}\right) \tag{11}$$

where x_i and p_i denote the position and local attractor of the i-th particle, respectively. And p_i can be written as

$$p_i(t) = a \cdot pbest + (1-a) \cdot gbest \tag{12}$$

where a is the same as u, and so a is uniformly distributed number belongs to [0,1]. *pbest* and *gbest* present personal best position of the particles and global optimum position of the particles, respectively. In addition, by defining mean best position (mbest), the expression of parameter L can be derived as follows [18-20]

$$L(t) = 2\alpha \left| mbest_i(t) - x_{id}(t) \right| \tag{13}$$

in which

$$mbest(t)=\frac{1}{M}\sum_{i=1}^{M} pbest(t) \tag{14}$$

$$\alpha=\frac{(1-0.5)\cdot(t_{\max}-t)}{t_{\max}}+0.5 \tag{15}$$

where α is just a parameter of QPSO, *t* is the number of iterations and *mbest* is the average of the optimal location that all particles have searched in the local.

QPSO transforms the node localization problem into the optimization problem. In the process of searching, the mean square error is used to be the fitness function of QPSO [21-23]. It is required to minimize this fitness function by multiple iterations. To adjust multi-hop HWSN , a weight is introduced into the fitness algorithm to improve the QPSO, and then the calculated global optimum position of the particles through using iterative calculation will be closer to real nodes coordinate. Therefore, the fitness function, aiming at multi-hop HWSN localization problem, is formulated as

$$fitness(x,y)=\sum_{i=1}^{n}\eta f_i^2 \tag{16}$$

in which

$$f_i=\left|\sqrt{(x-x_i)^2+(y-y_i)^2}-\hat{d}_{i-j}\right| \tag{17}$$

In the above equation, $\eta=(1/hop_i)^2$ represents weight values for each anchor node. Obviously, with the increase of the hops, the influence of weight values to fitness function gradually reduces. f_i is the difference between the distance of anchor node from particle and the estimation distance obtained by EHP approach. According to the results of the analysis above, the proposed algorithm based on EHP and QPSO are given as

Algorithm 1 Proposed localization algorithm for multi-hop HWSN.

Input: initialization N, N_a, anchor node coordinates (x_i, y_i), all sensor nodes' communication radius r, node density λ, the size of swarm M, the position of each particle, the maximum number of iterations t_{max}.

Output: unknown node coordinates (x_j,y_j).

```
for i=1,2,…,N_a do
    for j= N- N_a,…,N do
  Compute first-hop distance d^E_{i-k_1} and inter-node hop distance d^E_{k_{m-1}-k_m} by equation (8);
  Compute and the last-hop distance d^E_{k_m-j} according to equation (9);
    end for
end for
Obtain the estimation distance \hat{d}_{i-j} by equation (1);
Calculate the fitness function value for each particle by equation (16);
Compute the values of pbest and gbest;
for t=1,2,…, t_max do
```

```
   Compute α by equation (15);
   Compute mbest by equation (14);
for j=1,2,…, M do
    Update position of the particle;
    Compute fitness by equation (16);
    if pbest(t)<pbest(t-1)
    Update pbest;
    end if
end for
Compute gbest;
if gbest(t)<gbest(t-1)
    Update gbest;
end if
end for
```

4. Experimental Results and Analysis

In this section, the proposed method is compared with traditional and novel approaches for HWSN such as Amorphous [24-25], DV-hop [26], LAEP [27] and EHP [10]. Moreover, to verify the effectiveness of the algorithm, we compare QPSO algorithm with PSO algorithm in terms of localization accuracy and energy consumption. To evaluate the experimental results objectively, experimental parameters are tuned under the same condition, as **Table 2** shows. All experimental results are obtained by averaging over 100 trials. Note that the CPU times were obtained by running the Matlab code on a DELL computer with Intel (R) Core (TM) i7-6700 CPU, 3.40 GHz, 16.0 GB RAM, with Matlab 2014(a) on Windows 10 (64-bit operating system) in all experiments.

In this paper, we propose the evaluating indicator to estimate a measure of localization accuracy, i.e., the normalized root mean square error (NRMSE) which is defined by

$$NRMSE = \sum_{j=1}^{N_u} \frac{\sqrt{\left(x_j - \hat{x}_j\right)^2 + \left(y_j - \hat{y}_j\right)^2}}{N_u \cdot r_j} \tag{18}$$

where r_j is communication radius of the unknown node j, N_u is the number of the unknown nodes and $\left(\hat{x}_j, \hat{y}_j\right)$ is estimation value of coordinates $\left(x_j, y_j\right)$ of the unknown nodes.

Table 2. Simulation parameters

Parameter	Value
S	100×100 m^2
N_a	20 or 10:5:45
λ	0.01:0.01:0.06
N	100:100:600
r_i	6-30
M	50
t_{max}	150 or 0:10:500

4.1 Comparing with classical methods

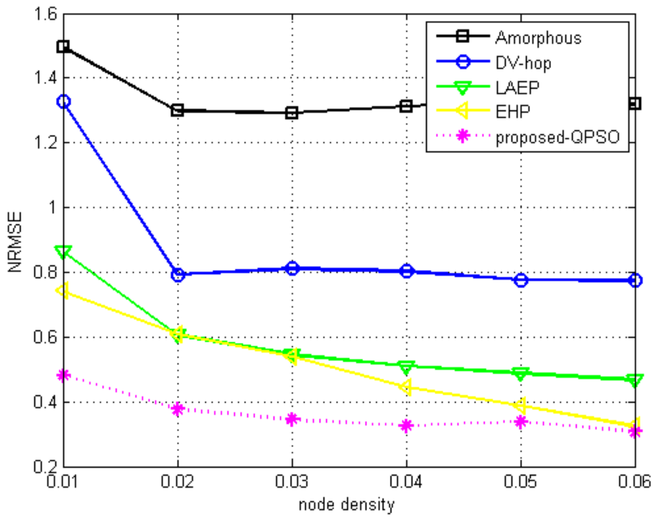


Fig. 4. NRMSE vs. node density in HWSN

Fig. 4 illustrates that the positioning error decreases with increasing node density. It is due to that the connectivity is improved with the increase of node density. The proposed algorithm shows a major decline and then a slow downtrend when node density is greater than 0.03. Its *NRMSE* is less than traditional and novel localization algorithms under various node densities. Thus, the proposed algorithm obviously improves localization accuracy, especially for the situation of low network node density.

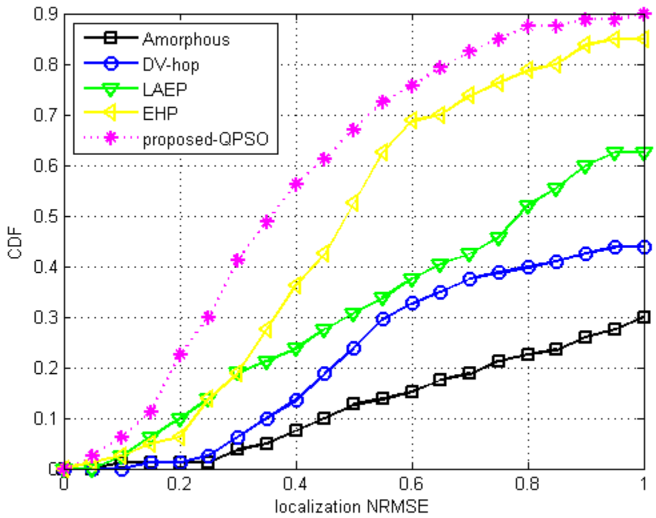


Fig. 5. localization NRMSE 's CDF for different localization methods in HWSN

Fig. 5 depicts the localization NRMSE's CDF for different localization methods under the condition that node density is 0.01. It shows that the NRMSE's CDF in the interval of 0.4 are 0.5625, 0.3625, 0.3275, 0.1350 and 0.0750 by using the proposed algorithm, EHP, LAEP, DV-Hop, and Amorphous, respectively. This further demonstrates the superiority of the proposed algorithm.

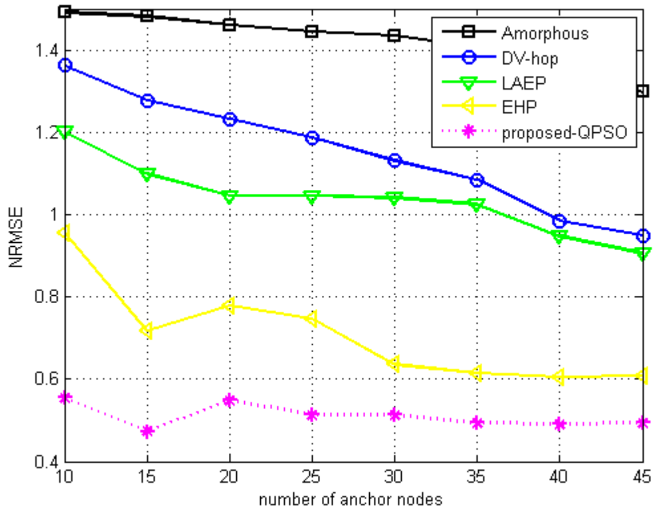


Fig. 6. NRMSE vs. number of anchor nodes in HWSN

Fig. 6 plots the localization NRMSE versus number of anchor nodes in HWSN With increasing the number of anchor nodes, the positioning error has been reduced in general when other conditions remain unchanged except for node density (i.e., λ=0.01). A comparison of the results from **Fig. 4** to **Fig. 6** indicates that it is important to reasonably determine ANs' communication radius and node density for improving the localization accuracy.

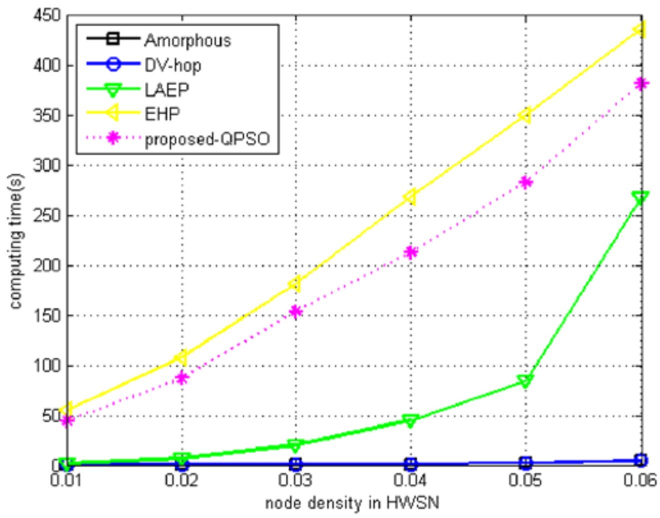


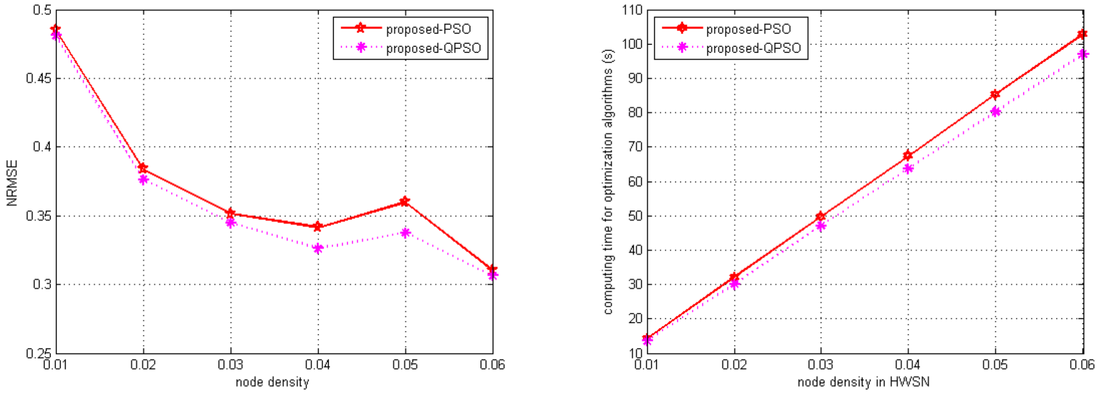
Fig. 7. time-consuming vs. node density in HWSN

In **Fig. 7**, we analyze the computational complexity of the localization algorithms. Experimental result indicates that among the localization approaches, energy consumption of the proposed algorithm is between EHP approach and classical approaches (i.e. Amorphous, DV-hop and LAEP). However, **Fig. 4** shows that classical approaches are inapplicable for HWSN due to large localization error. Noting that, for EHP approach, the work in [11] is actually an improved version of the work in [27] to adapt the heterogeneous network. Unfortunately, the complexity of the algorithm greatly increased because that one way makes the amount of computation huge due to the expression complexity of $F_{Z|X}(z)$, the other adds overhead because $F_{Z|X}(z)$ is determined by training during the improvement process. In this paper, our proposed algorithm can effectively reduce power cost as shown in **Fig. 7**.

4.2 Quantum Particle Swarm Optimization

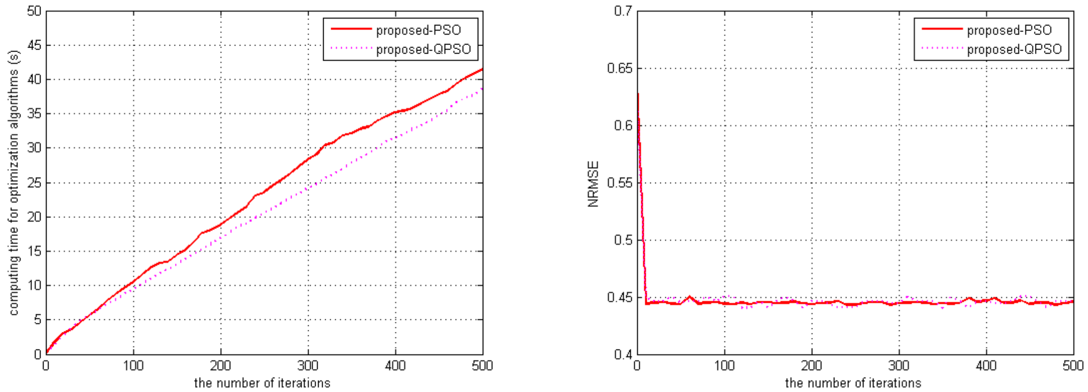
The comparison of PSO and QPSO algorithm for HWSN is shown in **Fig. 8** and **Fig. 9**, in which **Fig. 8** plots the localization NRMSE and energy consumption in different density sensor nodes, respectively. The simulation results show that QPSO algorithm has better convergence accuracy and higher evolution velocity compared with PSO algorithm.

Fig. 9 illustrates the energy consumption and localization NRMSE with different iteration numbers. As seen from **Fig. 9**, compared with PSO algorithm, the QPSO algorithm achieved satisfactory result in HWSN, the computation time is shortened and optimization effect is better with 0~500 iteration computation. In addition, the optimization algorithms (i.e., both PSO algorithm and QPSO algorithm) are effective to ensure that the less number of iterations, the higher accuracy in multi-hop HWSN localization.



(**a**) (**b**)

Fig. 8. Results with different node density: (**a**) NRMSE vs. node density for PSO and QPSO (150 iterations); (**b**) computing time vs. node density for PSO and QPSO (150 iterations)



(**a**) (**b**)

Fig. 9. Results with different iteration number: (**a**) computing time vs. the number of iterations; (**b**) NRMSE vs. the number of iterations

The result of Matlab simulation proves the feasibility of the proposed algorithm. The proposed algorithm not only has less error than other algorithms in dense HWSN, but also can be utilized in a sparsely distributed HWSN. Moreover, QPSO improves the efficiency and localization accuracy.

5. Conclusion

In this paper, a novel range-free localization algorithm based on QPSO is presented for multi-hop HWSN localization. We utilize the modified distance estimate method based on expected hop progress to reduce the computational complexity. In addition, QPSO algorithm which complies with the heterogeneous nature of WSNs is proposed successfully to optimize the coordinates of UNs. The proposed algorithm outperforms the state-of-the-art range-free ones in terms of localization accuracy and energy consumption.

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