Employing PSO to Enhance RSS Range-based Node Localization for Wireless Sensor Networks

by

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Abstract —

Wireless sensor networks (WSNs) usually employ different ranging techniques to measure the distance between an unknown node and its neighboring anchor nodes, and based on the measured distance to estimate the location of the unknown node. In its operation, a range-based localization scheme uses either trilateration or multilateration algorithms to obtain such range information. To trim down the hardware cost, some bring in iterative multilateration but encounter two problems (1) unable to localize unknown nodes with insufficient anchor nodes, and (2) the iterative process may build error accumulation. For improvement, this paper presents a new localization scheme, the key design of which is to improve localization success ratios by using the location data of remote anchors（provided by the closest neighbor nodes of an unknown node) to calculate the locations of unknown nodes with insufficient anchor nodes. The new scheme meanwhile employs the PSO algorithm to increase localization accuracy and the DV-distance approach to further boost up the success ratios of localization. Experimental evaluation shows that our new scheme performs constantly better than related target schemes either in increasing the localization success ratios or in decreasing location errors at reduced cost.

Keywords —

Wireless sensor networks (WSN), radio signal strength (RSS) ranging techniques, node localization schemes, particle swarm optimization (PSO), performance evaluation.

1 Introduction

Node localization algorithms for WSNs can be categorized as range-free and range-based. Range-free algorithms use connectivity among anchor nodes, not ranging techniques, to estimate the locations of unknown nodes. Range-based algorithms usually employ such ranging techniques [1] as Time of Arrival (TOA), Time Difference of Arrival (TDOA), Angle of Arrival (AOA) or Radio Signal Strength (RSS) to measure the distance (or angles) between an unknown node and its neighboring anchor nodes, and based on the measured distance to estimate the unknown node's location. In operations, the range-based localization schemes will use trilateration or multilateration algorithms to obtain the desired range information and then localize the unknown node. To reduce the needed density/number of anchor nodes (i.e., to cut down the hardware cost), some choose to use iterative multilateration which tends to cause two problems: (1) without enough anchor nodes, the locations of some unknown nodes will be inestimable and (2) the iterative process is likely to generate error accumulation. To solve the problems, some make use of collaborative multilateration [2], which nonetheless needs to guarantee anchor nodes are located at the edge of the network.

The main goal of this research is to construct an effective new node localization scheme able to locate unknown nodes accurately and successfully, i.e., able to reduce error accumulation and raise the localization success ratios. The unique design of our localization scheme is using the location data of remote anchors provided by the closest neighbor nodes of an unknown node with insufficient anchor nodes to calculate its location – so as to improve the localization success ratios. The other features of this new scheme include taking RSS as the ranging technique, employing the particle swarm optimization (PSO) algorithm [3,4] to obtain better calculation and adopting an approach similar to DV-distance [5] to further enhance localization

success ratios.

Our new scheme can actually work with any distance ranging technique to reduce location errors, but we choose to take RSS because RSS can support the most of wireless devices and help reduce hardware cost and power consumption in resource-constrained WSNs. On the other side, realizing node localization accuracy in wireless environments is subject to such influences as network topologies, numbers/positions of anchor nodes and external noise/obstacle interferences, we thus decide to bring PSO in – by building a suitable fitness equation to meet our needs and then utilizing its optimization feature to obtain better calculation and as a result higher localization accuracy. To further increase the localization success ratio, we then adopt an approach similar to DV-distance [5] to help unknown nodes with insufficient anchor nodes find their locations.

Experimental evaluation and comparison are conducted to examine the performance of our new scheme and other related schemes. The results show that, requiring fewer anchor nodes – i.e., less hardware cost, our PSO-based node localization scheme performs constantly better in reducing location errors as well as increasing localization success ratios.

2 Background Study

2.1 The Ranging Techniques

Time of Arrival (TOA) uses ultrasonic velocity and the arrival time between a transmitter node and the receiver node to calculate their distance. **Time Difference of Arrival (TDOA)** is similar to TOA except that it uses two media, the ultrasound and the RF medium, to generate the arrival time. TOA and TDOA may produce satisfactory localization accuracy but are constrained to function only within short transmission ranges (e.g., several meters only). Besides, the transmitter and the

receiver usually have to stay in the LOS (Line of Sight) situation to attain such high localization accuracy. The involved hardware cost of each node in a large-scale network must be carefully taken into account. **Angle of Arrival (AOA)** uses the angles between transmitters and receivers to estimate the distance and location of an unknown node. In operation, AOA needs antenna equipments, an extra cost, to obtain the needed messages, and its performance is also subject to changes in the outer environments. With the required hardware size, power consumption and cost, AOA is considered an infeasible ranging technique for WSNs.

Radio Signal Strength (RSS), by contrast, stands as a more practical and appropriate ranging technique for a wireless environment – because it requires no additional equipments and is thus more conserving in hardware cost and power consumption. The weak point of applying RSS to a WSN will be its high sensitivity to uncertain environmental elements (obstacles, noises and others), which is likely to generate larger errors than the other ranging techniques.

2.2 Radio Signal Strength (RSS)

Our new localization scheme can work with any ranging techniques but we decide to take in RSS because it stands out as a fit medium for measuring the distances between nodes in wireless environments. When a transmitter broadcasts a measurable power, the power strength reaching a receiver will decrease over growing distances, i.e., a receiver closer to the transmitter will receive a stronger signal, while a more distant receiver will receive a weaker one. The volume of signal strength thus becomes a proper distance indicator between the sensor nodes.

RSS, as mentioned, may produce more ranging errors than other ranging techniques because

(1) Radio reflection can bring up multipath propagation that will induce the fading phenomenon of signal strength.

(2) A pair of nodes may receive unequal measurement of RSS originating from each other – due to different hardware designs and changing ambient noises.

(3) Two nodes are not guaranteed to stay in an LOS situation.

To deal with these problems, we can generate a radio channel model, such as the following log-normal shadowing model in [6], to describe the fading behavior of signal propagation:

$$RSS(d) = P_T - PL(d_0) - 10\alpha\log_{10}\frac{d}{d_0} + X_\sigma$$

In this model, P_T is the transmitting power, $PL(d_0)$ is the path loss for a reference distance of d_0, and α is the path loss exponent. The noise in RSS is expressed as a Gaussian random variable of zero mean and σ standard deviation, $X_\sigma = N(0, \sigma^2)$. Whether in an ideal situation, the radio signal strength under forwarding will substantially follow certain fading patterns. For instance, when the received signal strength grows, the estimated distance interval between the receiver and the transmitter – even located in noisy surroundings – should be narrowing and a narrowing distance interval indicates a shrinking ranging error between the real and estimated distances.

Figure 1 shows an ideal signal fading model with no noise interference. Assume node *A* receives a message with signal strength between -90 ~ -80 dbm – whose distance (between *A* and the transmitter) would fall in interval d_1. If another node, say *B*, is located in the same environment and has received the same message with signal strength between -120 ~ -110 dbm, the distance between *B* and the transmitter would fall in interval d_2. As the figure shows, *A* sits closer to the transmitter than *B*, indicating d_1 will produce a more reasonable estimated distance (with smaller ranging errors) than d_2. An experimental study in [7] also proves that greater distances will

produce larger ranging and location errors (and vice versa) even if sensor nodes are located in a non-ideal environment. That is, with or without noise interference, the location of an unknown node can be obtained with a smaller/larger estimation error when its neighbor nodes stay closer to/farther from it. Following this observation, our scheme allows an unknown node to calculate its location based on the location data obtained from its closet neighbor nodes and meanwhile uses the PSO algorithm to reduce both the accumulative and location errors.

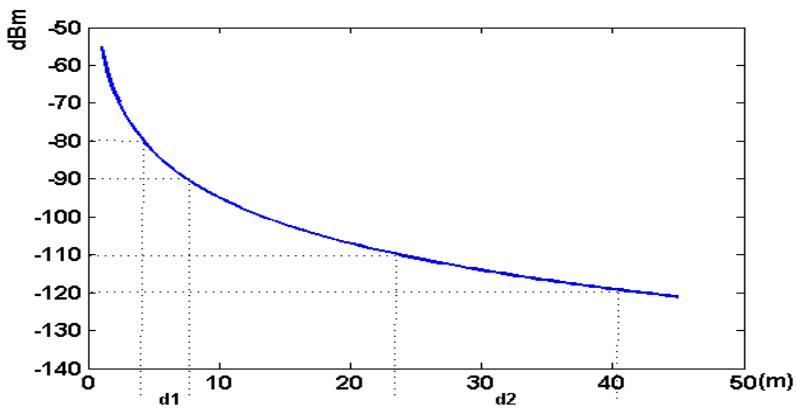

Figure 1. An ideal radio fading model.

2.3 Existing Localization Algorithms

Existing RF ranging techniques involve either RF-mapping or application of a signal fading model. **The RF-mapping** localization technique works by establishing a form of database of the signal strength behavior in the coverage area. The database will be obtained in the offline status by prior measurement using the access points (AP) at known locations. In the online status, an unknown node will collect the measurements broadcast by the AP and determine its own location by performing pattern matching on these measurements. **RADAR** [8] is an example of such a technique. Mainly applied in indoor environments, RADAR follows two steps to attain the localization of unknown nodes. It first collects the empirical measurements

of radio signal strength from the AP to establish a measurement database. Every mobile device randomly deployed in the coverage area then compares the signal characteristics between the existing database and the newly obtained measurement in the online status and moves on to estimate its own location according to the compared result. The main drawback for applying RADAR is obvious: It needs to establish an offline measurement pattern in advance and requires intensive measurement collections afterwards.

An Ecolocation Algorithm, similar to the RF-mapping technique, is introduced in [6] to reduce the impacts of path loss and obstacles. The algorithm first divides a given known area into several network grids and lets an unknown node in the network sends out a localization message. Multiple anchor nodes then record their RSS values for this message and determine the ordered sequence of the anchor nodes from high values to low values. The Ecolocation Algorithm goes on to scan the grids for a location which holds an ordered sequence of anchor nodes matching the measured sequence most correctly. The obtained location is then taken as the position of the unknown node.

Besides RF-mapping, **the radio fading model** can also serve as an RF ranging instrument. The radio fading model has in fact become a widely employed ranging technique in the wireless environments. It can be used to predict the distance between an unknown node and its neighbor nodes and thus to pinpoint the position of this unknown node according to the received signal strength and the path loss pattern.

The AHLoS Algorithm [2] is a typical example of using the signal fading model to estimate the locations of unknown nodes. The algorithm involves two ranging techniques, TDOA and RSS, and compares the accuracies of these two techniques to get the desired location. (Note that RSS may produce lower localization accuracy than TDOA when under the influence of interferences. TDOA however has its limits: It

functions only within shorter transmission ranges and in order to attain the desired localization accuracy, both the signal transmitter and receiver must stay in the LOS situation.) The AHLos system provides three localization styles, the atomic, iterative and collaborative multilaterations. A traditional multilateration localization algorithm, **the atomic multilateration** uses multiple neighbor nodes with known locations to find the position of an unknown node. **The iterative multilateration** applies the atomic multilateration in an iterative manner to locate the unknown nodes: An unknown node will become a new anchor node after successfully obtaining its location and the iterative process will go on until all unknown nodes find their locations. **The collaborative multilateration** first studies the collaborative location messages and the network topology with several anchor nodes and unknown nodes in it, and describes such information as an over-constrained or well-constrained set of quadratic equations with a unique solution.

As can be observed, AHLos can locate unknown nodes with a small amount of anchor nodes. In its iterative process, however, when an unknown node successfully obtains its estimated location, becomes an updated anchor node and broadcasts its location to the neighborhood, the location error resulting from measurement inaccuracy is also propagated to the neighbor nodes. Through such an iterative process, errors will accumulate and grow around the neighborhood. For improvement, the authors of AHLoS later develop **an n-hop multilateration localization algorithm** [9] to amend the two major weak points of AHLoS: The accumulation of errors and the iterative process being sensitive to the anchor node density. The n-hop multilateration algorithm uses collaborative multilateration to establish subgraphs which include both the anchors and unknown nodes and can be written as over-constrained or well-constrained sets of quadratic equations with a unique solution. The algorithm then uses the Kalman Filter to solve these equations and

obtain the estimated locations of the unknown nodes. This n-hop algorithm faces one problem: It must intentionally deploy some of the anchor nodes to the edge of the network to get complete constrained quadratic equations.

The Neural Network [10] puts the pre-training model in a sink. When a node collects ≧ 3 pieces of location information from its neighbors, it will return the collected information to the sink. The sink then puts the information into the pre-training model to get the node's estimated location. Localization by the pre-training model seems to work, but by offering only a general solution it can not fit every node.

The Modified DV-Hop [11] allows an unknown node to be located not only by anchor nodes but also by non-anchor neighbor nodes. That is, an unknown node with any transmission route will be able to receive location information from neighbors and to estimate its own coordinate when receiving enough information. The Modified DV-Hop can raise the localization success ratio but at high cost as it needs to flood location information of anchor nodes as well as non-anchor neighbor nodes.

The generic localized algorithm in [12] also aims to reduce error accumulation. To reduce the accumulation of estimation errors, the algorithm sets constraints for unknown nodes to become anchor nodes after obtaining their estimated locations. For the algorithm, an unknown node with less than three neighbor nodes within its transmission range will be determined as **an orphan node**, anchor nodes will be configured as gotFinal, and adjacent nodes will exchange data to get sufficient location messages. If an unknown node has less than three non-orphan neighbor nodes after the data exchange process, it will be taken as an orphan node and unable to locate its position. By contrast, if an unknown node has more than three "gotFinal" neighbors, it will randomly choose three of them to estimate its location. Such an algorithm apparently involves a good deal of calculation and communication cost.

3 The Particle Swarm Optimization (PSO) [3,4]

As using ranging techniques to determine distance tends to generate errors (due to factors such as noise interference, multipath propagation and so on) and the errors will lead to inaccurate localization of unknown nodes, most localization schemes can only specify a possible zone and then a possible position for an unknown node (based on the inaccurate information). For our new scheme, adopting the particle swarm optimization (PSO) has proven to yield more desirable localization accuracy than the target related schemes because each operation round of the PSO will narrow down the possible zone and lead us closer to the true solution and finally to a more accurate position.

A form of evolutionary computation established mainly on community wisdom, PSO can produce inestimable group behaviors through individual interaction rules. In its implementation, each particle stands for an independent search and takes the fitness value of the initial solution – which is randomly generated at the initial stage – as its optimal fitness value. When finding a better fitness value in any future generation (of the optimization process), a particle will update its original value into this new value and store this new optimal fitness value. Thus a particle will always record its up-to-date best fitness value in memory and go on to search for a potential better value based on the recorded information. For the particles of a group, such a searching and optimizing behavior is the performance of **the cognition-only model**.

Besides the cognition-only model, PSO also involves **a social-only model**. In performance of the social-only model, a particle will compare its current best fitness value with the group best fitness value to revise and update the latter value in each search. Each particle in the group then follows this revised new group value to modify its search velocity in the next searching generation. Thus generations after generations,

the repeated optimization searches engaged by the particle swarm will eventually produce a best group solution for the optimization problem under pursuit.

In our proposed localization scheme, we adopt a kind of **weighted PSO** which assumes the velocity of the particles has the inertia weight renewal [13, 14]. The advantage of bringing the inertia weight velocity to the search process is to find the best solution fast and stably. In the search process, the PSO first randomly generates a set of particles in the initial search stage and moves on to pursue the best solution for the target problem through the iterative optimization process. At each optimization attempt, a particle will change its searching direction based on two values: $\mathbf{P_{best}}$ (the particle's present best fitness value) and $\mathbf{G_{best}}$ (the group's current best solution resulting from the swarm's collective optimization memory). During the search process, each particle will update its searching speed and position according to the following two functions [12]:

$$v_i(t+1)=w \cdot v_i(t)+c_1 \cdot rand() \cdot (P_{ibest}(t)-x_i(t)) + c_2 \cdot rand() \cdot (P_{gbest}(t)-x_i(t)) \quad \ldots (1)$$

$$x_i(t+1)=x_i(t)+v_i(t) \quad \ldots (2)$$

t is the iterative step,

$v_i(t)$ and $x_i(t)$ each represents the velocity and position of particle i at step t,

$P_{ibest}(t)$ is the fittest position of particle i at step t, and

$P_{gbest}(t)$ is the fittest position of the group at step t.

$v_i(t+1)$ is the velocity of particle i at step $t+1$,

$x_i(t+1)$ is the position of particle i at step $t+1$,

$rand()$ is a random number between 0 and 1,

c_1 and c_2 are constants which are set to 2, and

w is the inertia weight between 0.1 and 0.5.

After $x_i(t+1)$ generating rounds, the PSO will use the fitness equation to evaluate the fitness value of each particle.

4 The Proposed PSO-based Localization Scheme

4.1 The Localization Process

Our localization scheme, which decides the location of an unknown node using the location data provided by its closest neighbor nodes, includes two modes: MODE 1 and MODE 2. After obtaining the number of existing neighbor nodes, an unknown node will follow either of the two modes to get its location.

MODE 1: The unknown node has enough (3 original/updated) neighboring anchors to estimate its position.

MODE 2: The unknown node does not have enough neighboring anchors to estimate its position.

```
1   While (not timeout) {
2      Listen for and collect anchor nodes' information
3      if (discover 3 or more anchor nodes in its neighborhood) {    //MODE 1
4         CALL procedure LOCALIZATION
5      }
6   }
7   //MODE 2
8   Get original anchor nodes' information from the packet broadcast by the closest neighbor anchors
9   if (discover 3 or more anchor nodes) {
10     CALL procedure LOCALIZATION
11  } else {
12     Set as an orphan node
13  }
14
15  Procedure LOCALIZATION
16  {
17     Use PSO to estimate the location and become an updated anchor node
18     Broadcast the estimated location and the location data of original anchor nodes
19     Localization complete and exit
20  }
```

Figure 2. The pseudo-code of our PSO-based localization scheme.

Figure 2 is the pseudo code of our PSO-based localization scheme. Initially, each anchor node will broadcast its ID and coordinate to the network. In lines 1-6 of Figure 2, each node keeps collecting the location information broadcast by neighbor anchors. When an unknown node discovers 3 or more (original/updated) anchor nodes in its

neighborhood, it will enter MODE 1 and use both the radio strength measurements and location messages of the neighbor anchors to estimate its location. In lines 15-20, an unknown node successfully gets its estimated location, becomes a new updated anchor node and will broadcast its estimated location along with the location data of the original anchor nodes.

On the other side, if an unknown node fails to find sufficient anchor neighbors to locate itself, it will enter MODE 2 to find its location. As in lines 7-10, an unknown node with less than 3 anchor neighbors can bring in multi-hop anchors (not updated ones) to help estimate its coordinate. As an unknown node that updates itself into an anchor will record its and its neighbor anchors' coordinates in memory, an unknown node with 1 or 2 anchors in MODE 2 can thus discover its location using such location data (including that of anchor nodes several hops away).

MODE 2 of our scheme actually performs in a way similar to **the DV-distance Algorithm** [5], except that it takes the direct (or shortest) distance between the closest anchor neighbor and the remote original anchor. For better illustration, an example of performing MODE 2 is given in **Figure 3**, where nodes A and E are the original anchor nodes, B, C and D are the updated anchor nodes and U is the unknown node. Under the DV-distance algorithm, U will collect coordinates and distances from A and E, and the distance between U and E will be an accumulation of $\overline{UB} + \overline{BC} + \overline{CD} + \overline{DE}$. By DV-distance, U will never compute its location in this case because it has only two original anchor neighbors A and E. But under MODE 2 of our scheme, B (an updated anchor) will record the location data of anchor node E and can thus compute the distance between itself and E directly (indicated by the dotted line in the figure), without detouring C and D. In calculating the location of U, such a design reduces not only the ranging distance but also the probability of error accumulation (because anchor E can provide a more accurate location coordinate than updated anchors C and

D). Thus under the PSO algorithm in MODE 2, U will eventually get its estimated location by the location messages of A, B and E – leaving out C and D.

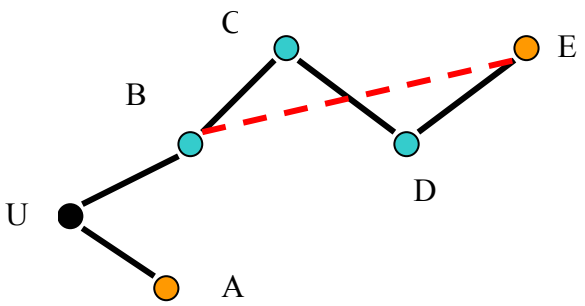

Figure 3. An example of performing MODE 2 in our scheme.

Note that in order to reduce the communication cost, our new localization scheme lets an unknown node broadcast only the location data of itself and the original anchors after it is updated into an anchor node.

4.2 Application of the PSO Algorithm

As stated, the localization process of our scheme employs the PSO algorithm to optimize and obtain the locations of unknown nodes. Originally, an unknown node will start performing PSO to search its location after collecting three or more location messages from the neighboring anchor nodes. Assume that unknown node u will engage PSO to estimate its coordinate (x_u, y_u), and R_i is the inexact ranging distance between u and its neighbor anchor node i. If the difference between the real and estimated locations of u (calculated from i) is described as an error equation e_i, e_i can be written as:

$$e_i = \left(R_i - \sqrt{(x_i - x_u)^2 + (y_i - y_u)^2} \right)^2 \quad \text{.....(3)}$$

In Equation (3), the square function is brought in only to make sure that the error

value is a positive number so that we can compare the value more conveniently. If node u has n neighbor anchor nodes, the above error equation will become

$$\sum_{i=1}^{n} e_i = \sum_{i=1}^{n} \left(R_i - \sqrt{(x_i - x_u)^2 + (y_i - y_u)^2} \right)^2 \quad \text{.....(4)}$$

To discover the estimated location (x_u, y_u), node u will randomly generate k particles (i.e., k random coordinates) as the initial population. Each of the k particles will compute the error value from the error equation and apply the PSO algorithm to attain the group best value, Gbest, which is to be taken as the estimated location of u. To improve the location error accumulation problem resulting from the iterative process of multilateration (when the ranging distances are inaccurate), we add a weighted value ($\frac{1}{R_i}$) to adjust the error equation as follows:

$$\sum_{i=1}^{n} e_i = \sum_{i=1}^{n} \left(R_i - \sqrt{(x_i - x_m)^2 + (y_i - y_m)^2} \right)^2 \times \frac{1}{R_i} \quad \text{.....(5)}$$

Recall that our discussion in Figure 1 confirms that localizing an unknown node by its closer neighbors will generate more accurate result. We therefore let a particle divide the error by the ranging distance between the corresponding anchor node and itself, and take the result as the weighted value. Using such a weighted value will constrain the estimated location of an unknown node into the vicinity of the real location (i.e., help bring the estimated location closer to the real location). Even with inaccurate ranging data, we can still use the shortest distance to constrain the estimated locations and reduce location errors.

In Equation (5), n is the number of neighbor anchor nodes, m is the particles from 1 to k and R_i is the ranging distance of the anchor nodes. During the searching process, each particle will compute the fitness value according to Equation (5) and update P_{best} by the location with the smallest error. Equation (5) can be used to eliminate the location error. The particle with the smallest location error is the fittest particle, i.e., closest to the real location. The location error is thus taken as the fitness

value, and G_{best} will be set as the P_{best} with the smallest fitness value.

After getting P_{best} and G_{best}, each particle will calculate its next position by Equations (1) and (2), and use the new location to re-calculate the fitness value and then update P_{best} and G_{best}. This iterative searching process will repeat until the convergence is reached. In our localization algorithm, the searching process will stop when the error between all particles drops below10^{-4} or when the searching process reaches 20 rounds – to conserve resources. Note that 10^{-4} is a value decided by experience. The value is in fact small enough to declare convergence. When all particles drop in such a small region and do not fall off, it indicates the region is not the local optimum.

Figure 4 illustrates how an unknown node locates itself by PSO. In this example, unknown node U gets 4 anchor nodes A_1, A_2, A_3 and A_4 within its communication range and holds the rough RSS distance measurements between itself and the 4 anchors, R_1=10, R_2 = 2, R_3 = 3 and R_4 = 10. After obtaining these measurements, U begins to search its location using PSO. It first randomly generates k particles in the search space, records their coordinates and uses Equation (5) to compute the error value of each particle. For example, the error value of a specific particle, say k, can be calculated as follows:

$$e_k = (R_1 - \sqrt{(x_{A_1} - x_k)^2 + (y_{A_1} - y_k)^2})^2 \times \frac{1}{R_1} + (R_2 - \sqrt{(x_{A_2} - x_k)^2 + (y_{A_2} - y_k)^2})^2 \times \frac{1}{R_2}$$
$$+ (R_3 - \sqrt{(x_{A_3} - x_k)^2 + (y_{A_3} - y_k)^2})^2 \times \frac{1}{R_3} + (R_4 - \sqrt{(x_{A_4} - x_k)^2 + (y_{A_4} - y_k)^2})^2 \times \frac{1}{R_4}$$

After the error values of all k particles are obtained, the particle with the smallest error value will be taken as the candidate situating nearest to the real location of U and selected as the local best solution in this generation. The same searching process repeats generations after generations to search for a more precise location of U until reaching convergence. (In Figure 4, the blue dot stands for the final estimated location

of *U*.) However, if we employ LSE (Least Square Estimation) to calculate the location of an unknown node, obvious location errors will appear due to distinct differences between the estimated and actual locations, which result from the very imprecise distance measurements.

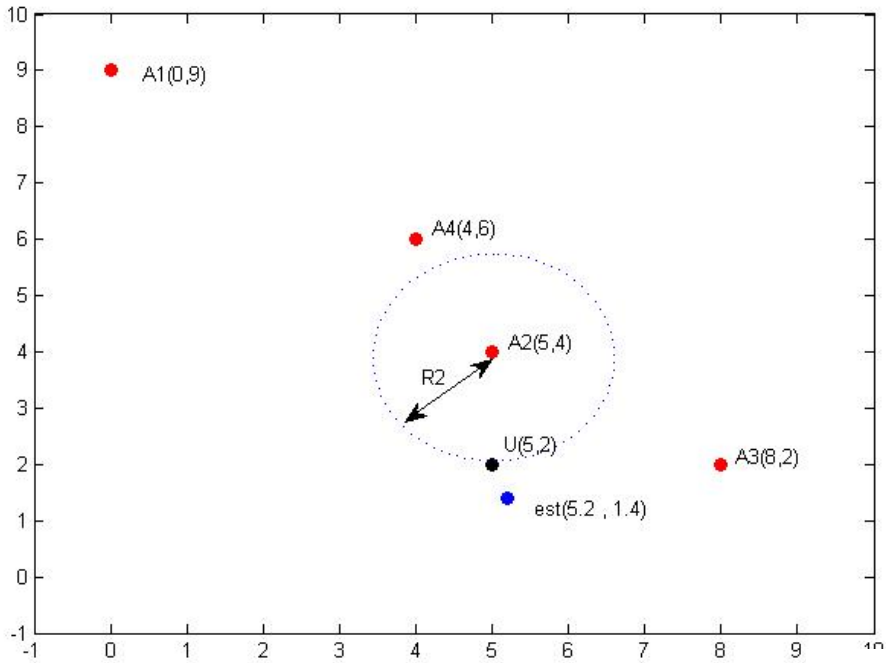

Figure 4. A localization example using the PSO algorithm.

5 Performance Evaluation

5.1 The Simulation Model

Simulation runs using the Matlab are carried out to evaluate and compare the performance of **our new scheme** and other related schemes, including **the Iterative Multilateration** (of AHLoS) [2], **the DV-distance Algorithm** [5], **the Ecolocation Algorithm** [6]**, the Neural Network** [10] **and the Modified DV-Hop** [11]. RADAR is not included because it has to establish the RSS database offline, which is not feasible for computerized simulation. Also excluded is the n-hop mulitilateration

algorithm which needs to deploy some anchor nodes to the edge of the network in order to get desirable localization – unlike our scheme that randomly distributes all nodes to the network. The genetic localization algorithm is also left out because it is similar to the iterative multilateration of the AHLoS system.

Simulation runs are conducted mainly in a 50m×50m wireless sensor environment, except those to evaluate the performance of our MODE 2 which are engaged in an extended area of 80m×80m with a maximum transmission range of 20m. Our simulation adopts the RF fading model; each collected result is the averaged value over 10 runs. Table 1 lists some typical values used in the simulation. These values are the best values decided over extensive simulation runs. If the fitness equation does not change, the parameter will work normally. The location error is defined as the ratio of (the distance between the estimate and real locations) to (the transmission range).

Table 1. Typical values of simulation parameters

Parameters	Typical values
The network scale	100
Transmission range $\boldsymbol{R}$	25m (Simulations 5.2.1 – 5.2.4)
Transmission power $\boldsymbol{P_T}$ **(dBm）**	0 dBm
Path loss exponent $\boldsymbol{\alpha}$	4
$\boldsymbol{P_L(d_0)}$	-55 dB (d_0=1m)
Standard deviation $\boldsymbol{\sigma}$	2-15
Number of particles $\boldsymbol{k}$	10
Unit distance of the grid (Ecolocation)	0.5m

5.2 The Simulation Results

5.2.1 The RSS sample times vs. location errors

Figure 5 gives the number of RSS samples vs. location errors for the schemes, including ours which is plotted as PSO. This simulation takes 10% of the deployed nodes as the anchor nodes. The result shows that due to accumulated distances, **the DV-distance Algorithm** produces increasing location errors regardless of the number of RSS samples. **The Ecolocation Algorithm** needs a large number of anchor nodes to attain good performance – when the number of anchor nodes decreases, so does its performance. The Neural Network yields the same performance over different RSS samples because it locates the unknown nodes by the pre-training model whose accuracy will not be affected by RSS samples. **The Iterative Multilateration** and **our PSO scheme** are shown to produce more accurate results even under increased RSS samples. Our scheme actually generates the smallest location errors thanks to its unique feature designs, such as localizing an unknown node by the location data of remote anchors (provided by the closest neighbors) and using the PSO algorithm.

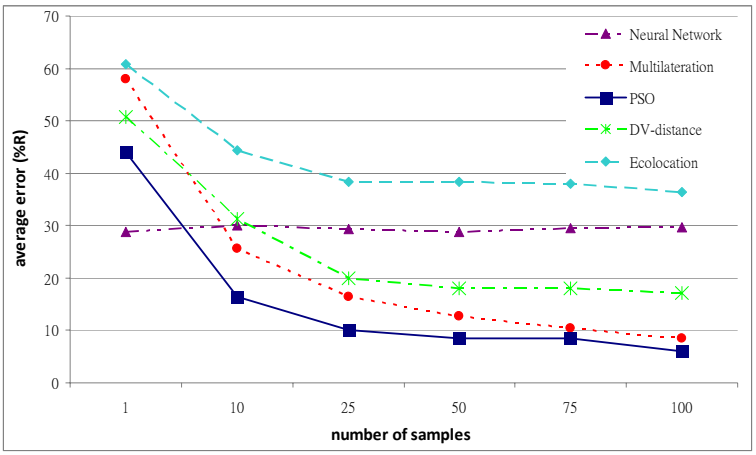

Figure 5. The number of RSS samples vs. location errors.

5.2.2 Network sizes vs. location errors

Figure 6 displays that in a fixed area of 50m×50m with 10% of nodes being anchors, different network sizes (with 40 to 150 nodes) will cast different impacts on

the average location errors for the four schemes. As the results exhibit, with fewer anchor nodes in the system, **DV-distance** produces distinctively larger errors because it needs more estimated distance measurements to locate an unknown node and is therefore more vulnerable to error accumulation. Modified DV-Hop can locate unknown nodes by both anchors and non-anchor neighbors but is still affected by error accumulation. Neural Network performs stably in any networks thanks to the pre-training model. With a robust enough pre-training model, it can neutralize any environmental influences. By contrast, having 10% of anchor nodes in the system proves insufficient for **Ecolocation** to turn over favorable performance, either in small or large networks. **Iterative Multilateration** generates smaller errors than both DV-distance and Ecolocation but its average errors does not shrink explicitly with growing network sizes, indicating it remains affected by cumulative errors when under harsh noisy conditions. **Our PSO scheme** yields the best performance (i.e., the smallest errors) and the advantage gets even more obvious in larger networks thanks again to its employment of the shortest measured distance to estimate the locations of unknown nodes, which significantly reduces the probability of error accumulation.

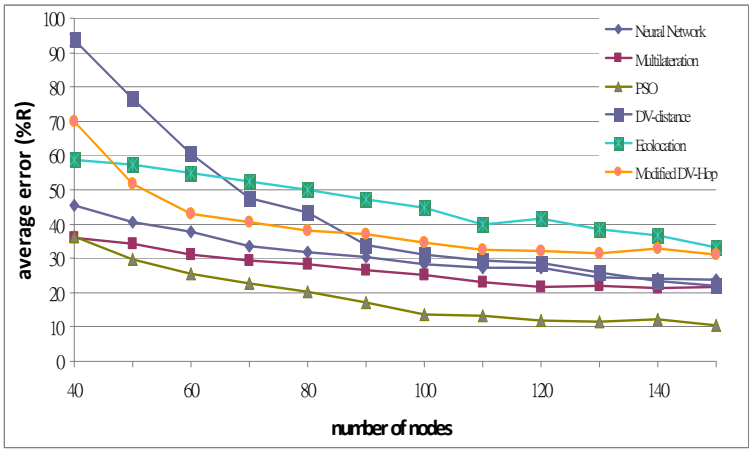

Figure 6. Network sizes vs. location errors.

5.2.3 The number of anchors vs. location errors

Figure 7 shows that different anchor ratios will influence the amount of location errors. Take **DV-distance** as an example. When the network has 10% anchor nodes, it generates bigger than 70%R error; when the anchor ratio increases to 20%, its average error decrease to around 30%R, and the decreasing trend slides to about 10%R error at anchor ratio = 70%. For **Iterative Multilateration** and **Modified DV-Hop**, taking the updated anchors as new anchors causes problems: No matter how many original anchors are deployed, some cumulative errors will always appear during the localization process. For **Neural Network** with the pre-training model, more anchor nodes will bring up better accuracy. Both **Ecolocation** and **our scheme** display a stable error-decreasing trend over growing anchor ratios. Our scheme performs especially well – it manages to produce the smallest errors at all anchor ratios, even without large numbers of original anchors.

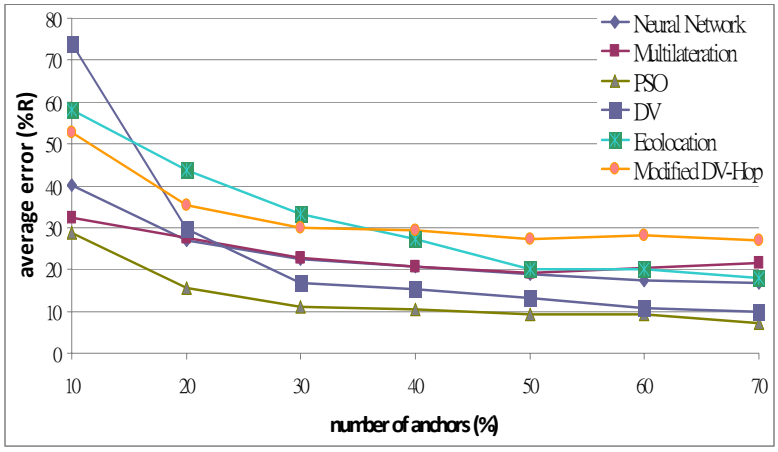

Figure 7. The number of anchors vs. location errors.

5.2.4 The noise standard deviation vs. location errors

Figure 8 specifies the relationship between noise standard deviations and location errors. When noise standard deviations increase, both **DV-distance** and **Ecolocation** fail to cut down location errors – because the former needs to accumulate distances while the latter lacks sufficient anchors to estimate locations. **Neural**

Network keeps stable performance because its pre-training model neutralizes the effect of noise. As for **Iterative Multilateration** and **our PSO scheme**, the location errors grow with noise standard deviations but in a more moderate trend. Note that our PSO scheme outperforms the others under all levels of noise standard deviations – it turns out notably smaller location errors because of its high estimation precision (from using the shortest distance measurement which helps cut back error accumulation).

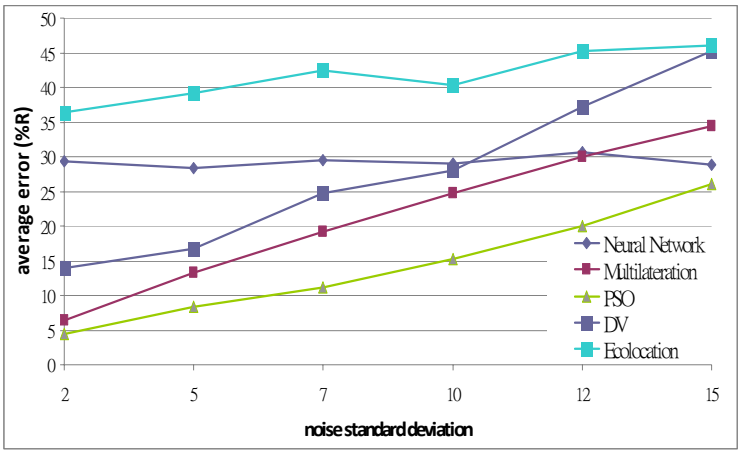

Figure 8. The relationship between noise standard deviations vs. location errors.

5.2.5 Localization success ratios vs. the numbers of anchors and location errors

The localization success ratio is the number of unknown nodes in a network which successfully obtain their locations over the total number of sensor nodes. In this simulation, we adopt an 80m×80m wireless sensor area with a 10% anchor ratio and a 20m maximum transmission range. The other parameters follow what is listed in Table 1 and the Ecolocation Algorithm is not included in this evaluation because it is not feasible for a large network with low anchor density. As **Figure 9** shows, in contrast to our PSO scheme and Iterative Multilateration, **DV-distance** yields distinctively higher localization success ratios in all situations. This is because

DV-distance can calculate an unknown node's location by only 3 exchanged location messages from neighboring nodes, thus enabling nearly all unknowns to attain their locations. The high localization success ratios are nevertheless gained at conspicuous cost: location errors resulting from accumulated distances also rise sharply. The localization success ratios of our scheme may not appear as high in some circumstances – because an unknown node in our scheme will broadcast the location data of itself and its neighbor anchors only *once* after being updated into an anchor node (in contrast to DV-distance which adopts *periodically* exchanged location messages). The point is, the updated anchors in our scheme are employed in an iterative way to help unknown nodes obtain locations with more accurate calculations, significantly reducing the location errors. In fact, when anchors increase, our scheme will yield as desirable success ratios as DV-distance, with much smaller location errors.

By MODE 2 of our scheme, unknown nodes can get enough location messages from anchor nodes several hops away and attain a better chance to locate themselves than by Iterative Multilateration. An unknown node nevertheless may employ the closest neighbor node which is an updated anchor to assist with distance measurement and location estimation, and thus brings up location errors. To give a better view on this situation, we plot in **Figure 10 "**the location error for each node" over a simulated network of 50 nodes with 8 anchors. In this figure, for those nodes with bigger distinct location errors, we are positive that they have involved certain updated anchor nodes in their location estimation process.

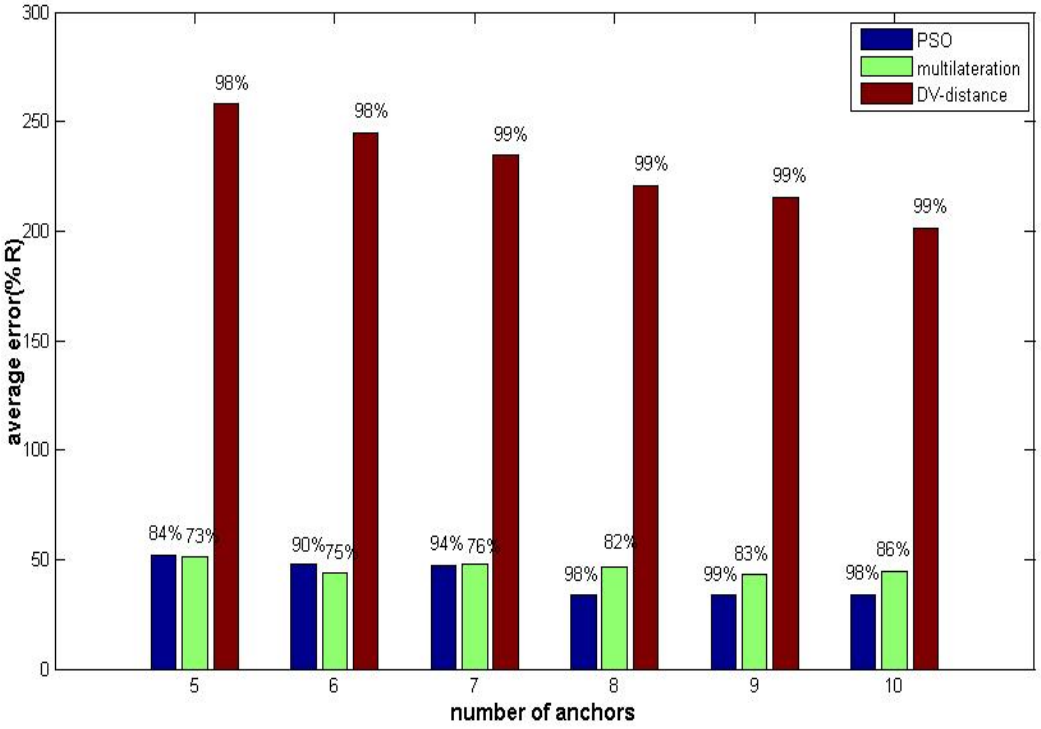

Figure 9. Localization Success ratios vs. the numbers of anchors and location errors.

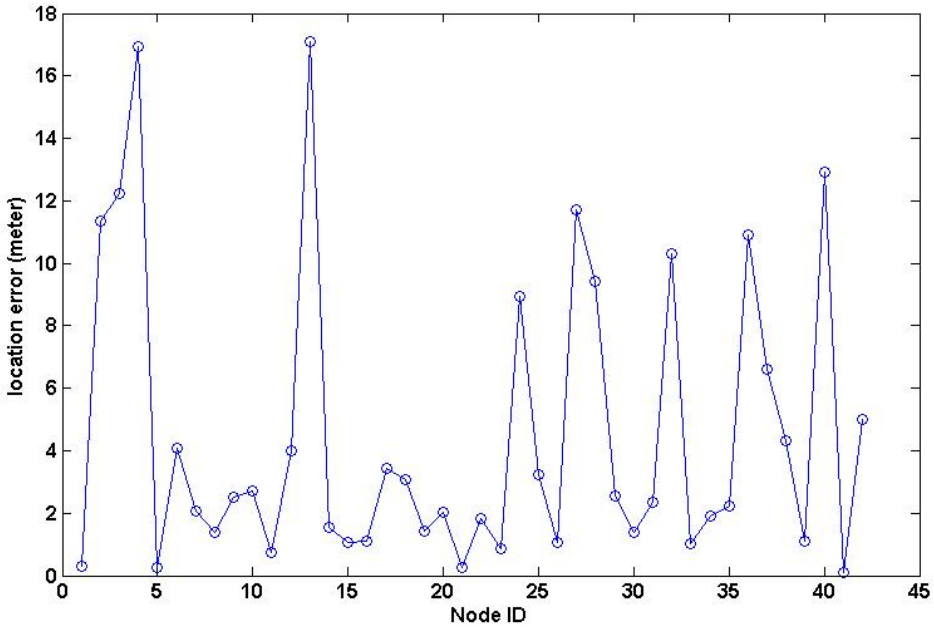

Figure 10. The location error for each node in a network of 50 nodes (with 8 anchors) under our scheme.

5.3 Computation complexity and overhead analysis

According to [15], a sensor node needs to do one 160-bit multiplication – which takes less than 3 ms, and one 160-bit addition – which takes less than 3 ms. For our new scheme, each PSO generation needs to do $4nk+5k$ additions, $5k$ multiplications and $4nk$ exponential operations (n = the number of neighbor anchors, k = the number of particles). As our PSO will generate at most 20 generations, a sensor node may thus consume approximately 20 sec (if n=3 and k=10) to complete localization – without causing overloading. Compared with other schemes, ours may take longer time to locate unknown nodes. We nevertheless consider such time consumption worthwhile when given the gain in reduced localization errors.

In our attempt to reduce cost, we do not flood information but adopt single-hop broadcasting. Nodes will not broadcast location information before successfully localized, and after being localized, they will broadcast only once. In contrast to DV-distance that maintains a table periodically, our new scheme apparently inflicts no higher cost.

6 Conclusion

This paper presents an effective new node localization scheme to locate unknown nodes in WSNs accurately and successfully. The major features of this new scheme include

(1) using the location data of remote anchors provided by the closest neighbor nodes of an unknown node with insufficient anchor nodes to calculate its location – so as to improve the localization success ratios,

(2) taking RSS as the ranging technique – because RSS can support the most of wireless devices and help conserve resources,

(3) employing PSO to optimize the calculation and estimation of node

locations and to attain better accuracy,

(4) adopting an approach similar to DV-distance to further enhance localization success ratios.

Experimental evaluation and comparison show that, requiring fewer anchor nodes (i.e., less hardware cost), our PSO-based node localization scheme constantly outperforms the other related schemes in diminishing location errors as well as increasing localization success ratios.

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