2008 Ninth International Conference on Parallel and Distributed Computing, Applications and Technologies

An Effective PSO-based Node Localization Scheme for Wireless Sensor Networks

Po-Jen Chuang and Cheng-Pei Wu
Department of Electrical Engineering
Tamkang University
Tamsui, Taipei County
Taiwan 25137, R. O. C.
E-mail: pjchuang@ee.tku.edu.tw

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 position of the unknown node. This paper presents an effective Particle Swarm Optimization (PSO)-based Localization Scheme using the Radio Signal Strength (RSS) ranging technique. Modified from the iterative multilateration algorithm, our scheme is unique in adopting the location data of remote anchors provided by the closest neighbor anchors of an unknown node to estimate the unknown node's position and using the PSO algorithm to further reduce error accumulation. The new scheme meanwhile takes in a modified DV-distance approach to raise the success ratios of locating unknown nodes. Compared with related schemes, our scheme is shown through simulations to perform constantly better in increasing localization success ratios and decreasing location errors -- at reduced cost.

1. Introduction

Current node localization algorithms for the wireless sensor networks (WSNs) can be categorized as range-free and range-based. Involving no ranging techniques, range-free algorithms mainly use connectivity among the anchor nodes to estimate the positions of unknown nodes. Range-based algorithms will 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 position of the unknown node. Among these ranging techniques, RSS stands as a more practical and appropriate alternative. In a wireless environment, it is desirable to involve RSS to measure the distances between nodes so as to locate unknown nodes – because requiring no additional equipments, RSS will be more conserving in hardware cost and power consumption. However, there is one apparent weakness for applying RSS to a sensor network: It is highly sensitive to uncertain environmental elements, such as obstacles, noises and others, and is therefore likely to generate larger errors than the other ranging techniques.

The RSS localization schemes usually use trilateration or multilateration algorithms to obtain the range information and following the obtained range measurement to calculate the position of an unknown node. Some algorithms involve iterative multilateration to reduce the needed density (number) of anchor nodes in the network in order to trim down the hardware cost. Iterative multilateration tends to cause two problems: (1) Without enough anchor nodes, the positions 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 which adopts RSS as its ranging technique and is able to reduce error accumulation and the number of unknown nodes (i.e., raise the localization success ratios) for the wireless sensor networks. The proposed Particle Swarm Optimization (PSO)-based Localization Scheme, a

978-0-7695-3443-5/08 $25.00 © 2008 IEEE
DOI 10.1109/PDCAT.2008.73

modified design of the iterative multilateration, determines the estimated position of an unknown node using the location data of remote anchors provided by the closest neighbor anchors of the unknown node to decrease accumulative errors. In raising up the estimation accuracy, our new scheme adopts the PSO algorithm [3,4] to obtain better calculation and as a result fewer estimation errors during the localization process. Our scheme meanwhile employs an approach similar to the DV-distance [5] to help unknown nodes with insufficient anchor nodes find their positions, further increasing the success ratios of localization. Experimental evaluation is conducted to examine the performance of our new scheme and other related localization schemes. The collected results show that when compared with related schemes, our PSO-based scheme requires a smaller number of anchor nodes (i.e., less hardware cost) but performs constantly better in cutting back location errors and increasing node localization success ratios for WSNs.

2. Existing node localization schemes

The Ecolocation Algorithm [6] 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.

The AHLoS Algorithm [2] is a typical example of using the signal fading model [6,7] 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 (Line Of Sight) 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 an updated 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 the positions of 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* [8] 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 Generic Localized Algorithm in [9] also aims to reduce error accumulation. To reduce the accumulation of estimation errors, the algorithm sets constraints for unknown nodes to become updated 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, updated 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.

Observing the above RSS node localization schemes, we realize that node localization accuracy in wireless environments is subject to the influence of certain factors, including the topology of the network, the numbers and positions of anchor nodes, and external environmental impacts (such as noises, obstacles and so on). Taking these factors into consideration, this paper comes up with a new and effective localization scheme which is modified from the iterative multilateration and is called *the PSO-based Node Localization Scheme*. The PSO-based scheme can reduce both the accumulative errors and location errors as it determines the estimated position of an unknown node using the location data of remote original anchors provided by its closest neighbor anchors and also using the PSO algorithm. Besides, to increase the success ratios of localization, our new scheme chooses to use an approach similar to the DV-distance Algorithm to help unknown nodes which can not conveniently obtain sufficient location messages search and find their locations.

3. The Particle Swarm Optimization (PSO)

A form of evolutionary computation established mainly on community wisdom, the PSO can produce inestimable group behaviors through individual interaction rules [3,4]. 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 [10, 11]. 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: P_{ibest} (the particle i's present best fitness value) and P_{gbest} (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 [11]:

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

$$x_i(t+1)=x_i(t)+v_i(t)$$

In the functions,
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 best fitness value of particle i at step t,
$P_{gbest}(t)$ is the best fitness value 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.

4. The Proposed Localization Scheme

4.1. The localization process

As mentioned in Section 2, our localization scheme estimates and decides the location of an unknown node using the location data of remote anchors provided by its closest neighbor anchors. Our new scheme includes two modes, MODE 1 and MODE 2. After obtaining the number of existing neighbor nodes, an unknown node will follow either of the modes to get its location.

MODE 1: The unknown node has sufficient (three original or updated) neighboring anchors to estimate its position.

MODE 2: The unknown node has insufficient neighboring anchors to estimate its position.

Initially, each anchor node will broadcast its ID and coordinate to the network and check if any updated anchor nodes (i.e., unknown-becoming-anchor nodes) emerges in its neighborhood. If any, the anchor node needs to send out its information to this updated anchor node. When an unknown node discovers three or more (original or 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. An unknown node successfully gets its estimated location then becomes an updated anchor node and will broadcast its estimated location along with the recorded location data of its neighboring anchor nodes to the network.

On the other hand, if an unknown node fails to find sufficient anchor neighbors to help locate itself, it will enter MODE 2 to find its position. In MODE 2, an unknown node with less than three anchor neighbors can bring in remote anchor nodes (not updated anchors) to help estimate its coordinate. Recall that the unknown nodes which update themselves into anchor nodes will record their coordinates and the coordinates of their neighbor anchors in memory. An unknown node with one or two anchors in MODE 2 can thus discover its location using such location data (including the data of anchor nodes several hops away). Note that in MODE 2 of our scheme, an unknown node with insufficient anchor neighbors can still estimate its location by using the location data of remote anchors provided by closest neighbor anchors of the unknown node. In other words, by performing MODE 2 of our new scheme, we can help orphan nodes (unknown nodes with less than three anchor neighbors) locate their positions. This is indeed an important contribution other localization schemes fail to reach.

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 1, where nodes A and E are the original anchor nodes, nodes B, C and D are the updated anchor nodes and node 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 $\overline{UB}+\overline{BC}+\overline{CD}+\overline{DE}$. (With the DV-distance, Node U will never compute its location in this case because it has only two original anchor neighbors A and E.) While under MODE 2 of our scheme, node B – which is 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 by 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 node E can provide a more accurate location coordinate than updated anchor nodes C and D). Thus under the PSO algorithm in MODE 2 of our scheme, node U will eventually get its estimated location based only on the location messages of nodes A, B and E (leaving out C and D).

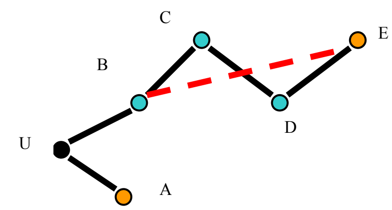

Figure 1. An example of performing MODE 2 in our scheme.

Note that in order to reduce the communication cost, our new localization scheme lets an unknown node broadcast the location data of itself and its neighbor anchors only 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 the unknown nodes. An unknown node will start performing the PSO algorithm to search its location after collecting three or more location messages from the neighboring anchor nodes. Assume that unknown node u will engage the PSO algorithm to estimate its coordinate (x_u, y_u), and Ri is the inexact ranging distance between u and its neighbor anchor node i. If the difference between the real location and estimated location of u (calculated from i) is described as an error equation e_i, e_i can be written as:

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

If node u has n neighbor anchor nodes, the above error equation will become

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

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, P_{gbest}, which is to be taken as the estimated location of u. To reduce the location error accumulation resulting from the iterative process of multilateration (when the ranging distances are inaccurate), we adjust the error equation as follows:

$$\sum_{i=1}^{n} e_i = \sum_{i=1}^{n} \frac{\left(R_i - \sqrt{(x_i - x_m)^2 + (y_i - y_m)^2} \right)^2}{R_i} \quad \text{…… (3)}$$

In Equation (3), 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 search process, each particle will compute and find the smallest fitness value according to the coordinates and distances of its neighbor anchor nodes. That is, each particle, say i, will calculate its P_{ibest} depending on the condition of its neighborhood. The PSO algorithm actually involves calculation occurring in both the local (P_{ibest}) and global (P_{gbest}) neighborhoods. The local neighborhood contains only the particle itself. In the global neighborhood, however, the fitness values of all particles will be considered and compared to attain the P_{gbest} and this iterative searching process will repeat until the convergence is reached. In this paper, our new localization algorithm will stop the searching process when the error between all particles drops below 10^{-4}, to avoid entering local optimum.

Note that when computing the error equation to get the best fitness value, a particle has to divide the error by the ranging distance between the corresponding anchor node and itself, and takes 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 hence to reduce location errors.

Figure 2 illustrates how an unknown node locates its position under the PSO algorithm. In this example, unknown node U gets four anchor nodes A1, A2, A3 and A4 within its communication range and holds the rough RSS distance measurements between itself and the four anchor nodes, $R_1 = 10$, $R_2 = 2$, $R_3 = 3$ and $R_4 = 10$. After obtaining these measurements, node U begins to search its position using the PSO algorithm. It first randomly generates k particles in the search space, records their coordinates and then uses Equation (3) to compute the error value of each particle. For example, the error value of a specific particle, say k, will be calculated as follows:

$$
\begin{aligned}
e_k = & \left(R_1 - \sqrt{(x_{A1}-x_k)^2+(y_{A1}-y_k)^2}\right)^2 / R_1 + \\
& \left(R_2 - \sqrt{(x_{A2}-x_k)^2+(y_{A2}-y_k)^2}\right)^2 / R_2 + \\
& \left(R_3 - \sqrt{(x_{A3}-x_k)^2+(y_{A3}-y_k)^2}\right)^2 / R_3 + \\
& \left(R_4 - \sqrt{(x_{A4}-x_k)^2+(y_{A4}-y_k)^2}\right)^2 / R_4
\end{aligned}
$$

After the error values of all k particles are obtained, the particle with the smallest error value will be taken as the candidate who sits nearest to the real position of node 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 node U until reaching convergence. In Figure 3, the blue dot stands for the final estimated position of node U. However, if we employ LSE (Least Square Estimation) to calculate the position of the unknown node, we will find obvious location error because of the distinct difference between the estimated location and the actual location of the unknown node which results from the very imprecise distance measurements.

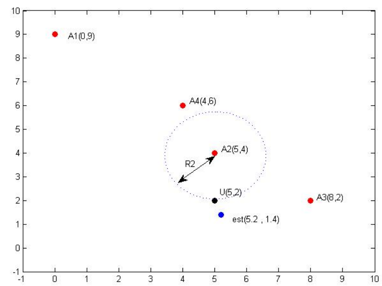

Figure 2. A localization example under the PSO algorithm.

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 localization schemes including the Iterative Multilateration (of AHLoS), the DV-distance Algorithm and the Ecolocation Algorithm. Excluded from performance comparison with our scheme is the n-hop mulitilateration localization algorithm which needs to deploy some anchor nodes to the edge of the network in order to get desirable localization – unlike our scheme which randomly distributes all sensor 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 an maximum transmission range of 20m. Our simulation adopts the RF fading model and each collected result is the averaged value over 10 runs. Table 1 lists some typical values used in the simulation.

Table 1. Typical values of simulation parameters

Parameters	Typical values
The network scale	100
Transmission range R	25m (Simulations 5.2.1 – 5.2.4)
Transmission power PT (dBm）	0 dBm
Path loss exponent α	4
PL(d0)	-55 dB (d0=1m)
Standard deviation σ	2-15
Number of particles *k*	10
Unit distance of the grid (Ecolocation)	0.5m

5.2. The simulation results

5.2.1. The numbers of RSS samples vs. location errors. Figure 3 gives the numbers of RSS samples vs. location errors for the four 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 result for the Ecolocation Algorithm manifests that the algorithm needs a large number of anchor nodes to attain good performance; thus when the number of anchor nodes decreases, so does its performance. Among the four schemes, the Iterative Multilateration and our PSO scheme are shown to produce more accurate results even under the increased number of RSS samples. Our scheme actually generates the smallest location errors thanks to its using the location data of remote anchors provided by the closest neighbor anchors of an unknown node and meanwhile using the PSO algorithm to estimate the location of the unknown node.

5.2.2. The network sizes vs. location errors. Figure 4 displays that in a fixed area of 50m×50m with 10% of the total nodes being the anchors, different network sizes (with 40 to 150 nodes) will cast different impacts on the number of location errors for the four schemes.

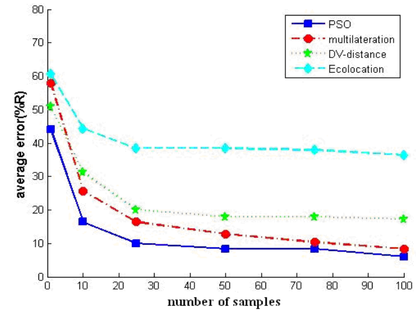

Figure 3. Numbers of RSS samples vs. location errors.

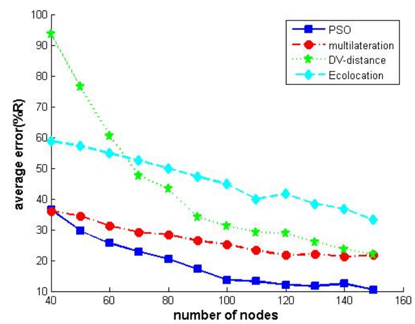

Figure 4. Network sizes vs. location errors.

As the results clearly exhibit, with fewer anchor nodes in the system, the DV-distance Algorithm will produce distinctively more errors because an unknown node needs to engage in more estimated distance measurements to find its location and is therefore more vulnerable to error accumulation. On the other hand, having 10% of anchor nodes in the system proves insufficient for the Ecolocation Algorithm to turn over favorable performance, either in a small or large network. The Iterative Multilateration generates fewer errors than both the DV-distance and Ecolocation Algorithms but its average number of errors does not shrink explicitly with the growing network size, indicating it remains affected by cumulative errors when under harsh noisy conditions. Our PSO scheme yields the best performance (i.e., the least number of errors) among all and the advantage gets even more obvious in larger networks thanks again to its adoption of the shortest measured distance to estimate the locations of unknown nodes, which significantly reduces the probability of error accumulation.

5.2.3. The numbers of anchors and location errors. Figure 5 demonstrates the fact that different anchor ratios will influence the amount of location errors. Take the DV-distance Algorithm as an example. When the network is with 10% anchor nodes, the DV-distance will generate more than 70 errors, but when the anchor ratio increases to 20%, its average errors decrease to around 30. The decreasing trend goes all the way down to about 10 errors at anchor ratio = 70%. For the Iterative Multilateration, taking the updated anchor nodes as the new anchors will cause problems: No matter how many original anchors are deployed in the network, a certain number of cumulative errors will always appear during the localization process. The Ecolocation Algorithm and our PSO scheme both display a stable error-decreasing trend over growing anchor ratios. Our new scheme performs especially well as it manages to produce the lowest number of errors at all anchor ratios − even without large numbers of original anchor nodes.

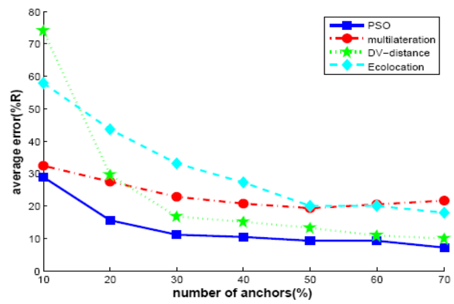

Figure 5. Numbers of anchors and location errors.

5.2.4. The noise standard deviation and location errors. Figure 6 specifies the relationship between noise standard deviation and location errors. As illustrated, when the noise standard deviation increase, both the DV-distance and Ecolocation Algorithms fail to cut down location errors – because the former needs to accumulate distances while the latter lacks sufficient anchor nodes to estimate locations. For the Iterative Multilateration and our PSO scheme, the numbers of location errors also grow with noise standard deviation but in a more moderate trend. In fact, under all levels of noise standard deviation, our PSO scheme outperforms the others by turning out notably smaller amounts of location errors − which comes from its high estimation precision (i.e., from using the shortest distance measurement which helps cut back error accumulation).

5.2.5. The 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 our simulation to examine the relationship among the localization success ratios, the numbers of anchor

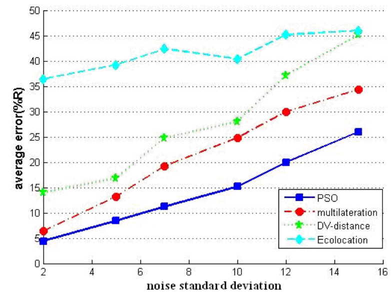

Figure 6. The relationship between the noise standard deviation and location errors.

nodes and location errors, we adopt an 80m×80m wireless sensor area with 10% anchor nodes and a 20m maximum transmission range. The other parameters follow what is listed in Table 1 and the Ecolocation Algorithm is not included for this evaluation because it is not feasible for a large network with low anchor density. The result in Figure 7 shows that in contrast to our PSO scheme and the Iterative Multilateration, the DV-distance Algorithm yields distinctively higher localization success ratios in all situations (i.e., in networks with different numbers of anchors). This is because, with only three exchanged location messages from the neighboring nodes (each message includes an anchor's coordinate and the accumulated distance), an unknown node in the DV-distance will be able to calculate its location, thus enabling nearly all unknowns to attain their locations. The high success ratios are nevertheless gained at conspicuous cost: The number of location errors resulting from the involved accumulated distances also rises sharply. The localization success ratios of our scheme may not appear as high as that of the DV-distance 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 while the DV-distance 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 their locations with more accurate calculations and estimations, significantly reducing the number of location errors. In fact, when the number of anchors increases, our scheme is able to yield as desirable success ratios as the DV-distance – with much decreased location errors.

In MODE 2 of our scheme, as mentioned, unknown nodes can get enough location messages from anchor nodes located several hops away, thus acquiring a better chance to find their locations than in the Iterative Multilateration. An unknown node nevertheless may

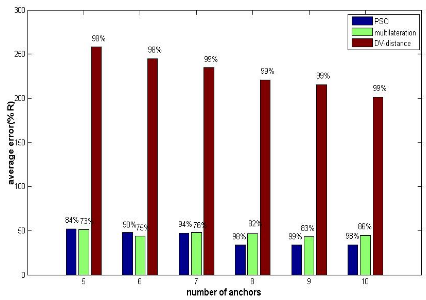

Figure 7. Localization success ratios vs. the numbers of anchors and location errors.

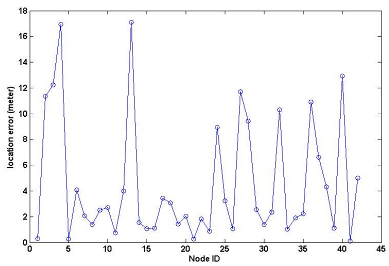

Figure 8. Location error placement in a network of 50 nodes (with 8 anchors) under our scheme.

employ the closest neighbor node which is an updated anchor to assist with distance measurement and position estimation, and thus brings up location errors. For better illustration, the placement of location errors in a simulated network of 50 nodes (with 8 anchors) is plotted in Figure 8. For those unknown nodes with more distinct location errors, we are positive that they have involved certain updated anchor nodes in their location estimation process.

6. Conclusion

This paper presents a PSO-based new node localization scheme to reduce error accumulation and increase the success ratios in locating unknown nodes in WSNs. Our new localization scheme, a modified design of the iterative multilateration, determines the estimated position of an unknown node using the location data of remote anchors provided by the closest neighbor anchors of an unknown node to estimate the unknown node's position. To attain more reliable estimation accuracy, the new scheme meanwhile adopts the PSO algorithm to optimize the calculation of node locations and reduce potential accumulative errors as well as final location errors. To further increase the success ratio of localization, our scheme involves an approach similar to the DV-distance to help orphan nodes which can not obtain sufficient location messages to search and find their locations. Experimental evaluation shows that when compared with related localization schemes, our PSO-based scheme performs constantly better in cutting down the number of location errors and increasing the localization success ratios – at reduced hardware cost

References

[1] G. Mao, B. Fidan, and B. D. O. Anderson, "Wireless Sensor Network Localization Techniques," *Computer Networks*, Vol. 51, No. 10, pp. 2529-2553, July 2007.

[2] A. Savvides, C.-C. Han, and M. B. Srivastava, "Dynamic Fine-grained Localization in Ad-hoc Networks of Sensors," *Proc. 7th Annual Int'l Conf. on Mobile Computing and Networking*, 2001, pp. 166-179.

[3] J. Kennedy and R. C. Eberhart, "Particle Swarm Optimization" *Proc. 1995 IEEE Int'l Conf. on Neural Networks*, 1995, Vol. IV, pp. 1942-1948.

[4] R. C. Eberhart and J. Kennedy, "A New Optimizer Using Particle Swarm Theory," *Proc. 6th Int'l Symp. on Micro Machine and Human Science*, 1995, pp. 39-43.

[5] D. Niculescu and B. Nath, "DV Based Positioning in Ad Hoc Networks," *Journal of Telecommunication Systems*, 22(1/4), pp. 267-280, 2003.

[6] K. Yedavalli, B. Krishnamachari, S. Ravula, and B. Srinivasan, "Ecolocation: A Sequence Based Technique for RF Localization in Wireless Sensor Networks," *Proc. 4th Int'l Symp. on Information Processing in Sensor Nnetworks*, 2005.

[7] K. Whitehouse, C. Karlof, and E. David, "A Practical Evaluation of Radio Signal Strength for Ranging-based Localization," *ACM Culler Mobile Computing and Communications Review*, 11, pp. 41-52, Jan. 2007.

[8] A. Avvides, H. Park, and M. B. Srivastava, "The *N*-hop Multilateration Primitive for Node Localization Problems," *Proc. 1st ACM Int'l Workshop on Wireless Sensor Networks and Applications*, 2002, pp. 112-121.

[9] S. Meguerdichian, S. Slijepcevic, V. Karayan, and M. Potkonjak, "Localized Algorithms in Wireless Ad-hoc Networks: Location Discovery and Sensor Exposure," *Proc. 2nd ACM Int'l Symp. on Mobile Ad Hoc Networking & Computing*, 2001, pp. 106-116.

[10] Y. Shi and R. C. Eberhart, "A Modified Particle Swarm Optimizer," *Proc. 1998 IEEE Int'l Conf. on Evolutionary Computation*, 1998, pp. 69-73.

[11] Y. Shi and R. C. Eberhart, "Parameter Selection in Particle Swarm Optimization," *Lecture Notes in Computer Science 1447 Evolutionary Programming VII*, pp. 591-600, Springer Berlin, 1998.