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Node Localization Method for Wireless Sensor Networks Based on Hybrid Optimization of Particle Swarm Optimization and Differential Evolution

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Abstract: *Directing at the locating problem of node location in wireless sensor network, a hybrid optimized method using Dynamic weight partical swarm optimization, Linearization method and Differential Evolution algorithms are proposed in this paper to enhance localization in Wireless sensor Network. Reducing the square error of estimated and measured distance between its adjacent anchor node and unknown node can guarantee a better localization accuracy in DWPSO compared to LM. This paper proposes DE algorithm is used to along with DWPSO to obtain the better localization accuracy. Simulation results indicate that this method provides smaller localization error, higher localization accuracy and better stability performance in DWPSOcompared to LM.*

Keywords: *localization**,** Wireless sensor Network,Dynamic weight Particle swarm optimization, Differential Evolution and Linearization method.*

I. Introduction

WSN is typically formed by organizing many sensor nodes in an adhoc manner. These nodes are intellect the physical features of the world. The sensors could be computing a different variety of properties including audibility, light, temperature and pollution etc. For guiding the queries and collecting data from the nodes are responsible by Base stations[1] .WSN node localization method by adopting heuristic algorithm, such as simulated annealing and genetic algorithm, which in turn proves the node localization effectiveness of heuristic algorithm.particle swarm optimization(PSO) [2], which has a good localization accuracy. The method has very good localization effect, notably if the measured distance error is big enough, but its stability and consumption remain to be improved. A new localization algorithm for WSN by combining disturbed and simple particle swarm optimization was proposed to solve the distance estimation errors problem of DV-hop algorithm [3]. DE algorithm is one algorithm based on population evolution. it has the advantages of simplification, good robustness,high-efficiency, high convergence rate, and so on. PSO algorithm is a kind of self-adaptive global optimization heuristic algorithm that has the advantages of simple algorithm, fast search easy adoption and so on [5]. Obviously PSO algorithm with good optimization and DE algorithm with strong strength in maintaining population diversification and searching ability are well complementary to each other [6]. Therefor, a hybrid-optimized WSN node localization method based on DE algorithm,comparison of PSO and LM algorithm are proposed in this paper.

II. RELATEDWORK

Node localization problem in WSN are actually the process of identifing the position coordinates of unknown nodes are achieved by using the distance information, and radius of wireless communications. The measured distance between unknown node and anchor node is not the real value. So unknown node position estimation can be treated as a kind of optimization, which minimizes the target function of localization error of anchor node to find out the position coordinate of unknown node. The major factor is an ranging error that affects the location error of the unknown node, and decrease the maximum error can meritoriously improve the localization accuracy. The mean square error of distance between anchor node and adjacent unknown node is defined as the fitness function of localization problem[7].
As shown below:

$$f_k(\hat{a},\hat{b}) = d_k - \sqrt{(a_k-\hat{a})^2+\left(b_k-\hat{b}\right)^2} \quad (1)$$

Where in ,(a_k, b_k) (k=1,2,...,M) is the actual coordinate of the ith anchor node, $(\hat{a}, \hat{b})$ is the evaluated coordinate of unknown node, $\sqrt{(a_k - \hat{a})^2 + (b_k - \hat{b})^2}$ is the valued distance between the kth unknown node and anchor node.$f_k(\hat{a}, \hat{b})$ is the error value between estimated and measured distance of the kth unknown node and that anchor node, and measured distance d_k is the distance between the kth anchor node and that unknown node. In reality the distance Measured between two nodes is not the real distance,therefore the combined form of gaussian error and real distance must be used for computing the real distance [8], i.e.

$$d_k = d_{kj}\,(1 + randn \times \eta)(2)$$

Where in d_{kj} is the measured distance,accuracy between error factor connected to real value between two distance

$$d_{kj} = \sqrt{\left(a_k - a_j\right)^2 + \left(b_k - b_j\right)^2}, \eta(3)$$

randn is the random variable subject to standard normal distribution , where the average value is '0' and square variance is '1'.In primary fitness function the weighted position information of nearest hop distance between the unknown node anchor node are introduced, the fitness function as shown below:

$$F_k(\hat{a}, \hat{b}) = \sum_{k=1}^{N} \alpha_k^2 f_k^2(\hat{a}, \hat{b})(4)$$

Where as, N is the number of nearest hop distance of anchor node to the unknown node. M=4,which is the minimum number of N,where α_i is the accuracy weight of measured distance between the unknown node and ith anchor node , which is in invers proportion with the shortest route hop count between the unknown node and ith anchor node and.The hop count can be calculated by using Dijkstra Algorithm[8].

III. Node localization Methods

1. Differential Evolution algorithm

Differential Evolution algorithm contains nondeterministic polynimial individuals and N dimensions available in each N-dimensional vector as affording to the problem. Differential Evolution employs mutations for each vector in one generation, produces a N dimension of donor vector[9] . To explain the donor vector There are different policies. In this paper, two different policies called DE/rand/1 as well-defined in Equation.4 and DE/current to best/rand/1 as well-defined in Equation.5 are considered. To design the trail vector Crossover operator has been used , as defined in Equation.6.The jrand is a arbitrarily chosen integer with in the limits of [1,NP]. Vectors are selected for next generation is based on greedy concepts chooses between trial and target vectors as defined in Equation 7. During the execution of self-adaptive DE algorithm, the difference of weighting issue F and crossover constant CR is used in the self-adapting control factor techiniques as shown in Equation 8 and Equation 9. The randj, jϵ {1, 2, 3, 4} indicate uniform arbitrary standards are varies from the limits [0, 1].To adjust CR and F the probabilities β_1 and β_2 are used correspondingly. 0.1, 0.1, 0.1, 0.9 values are assigned to the Constants β_1, β_2, Fl, Fu correspondingly. The mutation procedure is achieved After the control factor values are attained[10].

$$V_i^{(G)} = A_{r_1}^{(G)} + F \times \left(A_{r_2}^{(G)} - A_{r_3}^{(G)}\right)(4)$$

$$V_i^{(G)} = A_i^{(G)} + F \times \left(A_{best}^{(G)} - A_i^{(G)}\right) + F \times \left(A_{r_1}^{(G)} - A_{r_2}^{(G)}\right) \qquad (5)$$

$$u_{ij}^{(G)} = \begin{cases} v_{ij}^{(G)} & if\ rand(0,1) \le CR \quad or \quad j = j_{rand} \\ x_{ij}^{(G)} & otherwise \end{cases} (6)$$

$$x_{ij}^{(G)} = \begin{cases} u_i^{(G)} & if\ f\left(u_i^{(G)}\right) \le f\left(x_{ij}^{(G)}\right) \\ x_i^{(G)} & otherwise \end{cases} (7)$$

$$F_i^{(G+1)} = \begin{cases} F_1 + rand_1 \times F_u & if \quad rand_2 < \beta 1 \\ F_i^{(G)} & otherwise \end{cases} (8)$$

$$CR_i^{(G+1)} = \begin{cases} rand_3 & if \quad rand_4 < \beta 2 \\ CR_i^{(G)} & otherwise \end{cases} (9)$$

2. Particle swarm optimization

PSO is a one of the subset of Swarm Intelligence. The combination of local and global search methods are used in the PSO system. The particle position in search space is described based on element position and velocity parameters. As for problem-dependent fitness function each particle performance can be measured. With a a randomized velocity Each particle is moving towards the problem space. Best fitness is attained so far by itself and across its locality due to the position fascinated. To interchange experience between the particles, based on neighborhood topology two different forms of PSO can be used.Neighborhood of the particle is the complete inhabitants in the global version of the algorithm. neighborhoods of the particles completely saparated in the local versionof the algorithm.

$$V_{id}(l) = wV_{id}(l-1)C_1 r_1\left(P_{id}(q) - X_{id}(q)\right) + C_2 r_2\left(P_{gd}(q) - X_{id}(q)\right)$$

Move each particle to its new position

$$X_{id}(q+1) = X_{id}(q) + V_{id}(q+1)$$

Here, two random numbers i.e r1 and r2 are in a uniform distribution and with a limits of [0, 1]. W is the inertia of the particle which changes linearly in each iteration from 0.2 to 0.9.

3.PSO Based on DE Algorithm

Step 1: Set the initial parameters: population size is N , the iteration upper limit value is tmax, the control factor is λ , F represents the scaling factor, the solution precision is Ɛ, w start is the upper limit of Inertia weight value , w end is the lower limit of Inertia weight value,the acceleration parameter is set as 1c , 2c , mutation probability is set as CR.

Step 2: Divide the population into two populations as PSO and DE, set the initializing position in different areas.

Step 3: Calculate velocity and new location of the particle in PSO based on formula Step 2, Step 3 . Step 4: Calculate individual velocity and the new location in DE according to the formula Step 4, Step 5, Step 6.

Step 4: Calculate individual velocity and the new location in DE according to the formula Step 4, Step 5, Step 6.

Step 5: Select the best individual GbesGbest (DE) in PDE .

Step 6: Compare Gbest (PSO) and Gbest (DE) to get the better value and set it as the initial value in PSO and DE in the next step of evolution.

Step 7: If there is an individual that has stopped, the algorithm execute as the formula Step 7.

Step 8: Record the best value in all groups currently, when the algorithm reaches the iteration upper limit or meets the precision values we require. The algorithm terminates. Otherwise, proceed to Step 3 and continue.[11]

4.Distance localization algorithm

This algorithm is used to find the cumulative distance. Trilateration is used to compute the location of each unknown node by using three or more cumulative distance from anchors.The following steps are used to explain this algorithm[12].

1. Anchors localization with node ID and RSSI are enclosed in a beacon and flooded across the network by each anchor node.Each receipt node calculate the distance between its neighboring nodes based on the RSSI th eoretical model.After That they calculate the cumulative distance or the polyline-distance among hop to hop.
2. Node l and node m are the two anchors, anchor l becomes the polyline-distance to anchor m, it computes an Correction ratio(correction (l,m)) of polyline-distance(disl.m) to Straight-line (Disl.m) among the anchors l,m based on equation (10), and for the network correction broadcast that to the whole network.To caculate the amended distance (DisCorr k.l) between itself and anchor node the unknown node k receives the data from one anchor node i, it uses the polyline-distance (disk.l) from anchor nodes as specified in the following Equation (11):

$$Correction_{i,j} = \frac{\left(dis_{i,j} - Dis_{i,j}\right)/Hop_{i,j}}{Dis_{i,j}} \quad (10)$$

$$DisCorr_{k,i} = \frac{dis_{k,i}}{1 + Correction_{k,i} \times Hop_{k,i}} \quad (11)$$

Where, polyline-distance of unknown node k and anchor i is the $dis_{k.i}$ Correction $_{k.,i}$ is the correction of unknown node k and anchor i ,cumulative-distance of unknown node k and anchor l is the DisCorr k.l.Compute the unknown nodes location by maximum likelihood estimation or trilateration[13].

Linearization method (LM) suffers from accuracy in computing exact distance between bacons and unknown node. PSO is one of the heuristics based natural phenomena is used to overcome the difficult of convergence and accuracy of LM method. Because of performance and simplicity it is a tough contestant of other evolution based solution approaches like evolutionary strategy and genetic algorithm. inertia weight is the important parameter in PSO. In this paper, cognitive and constriction factor along with dynamic inertia weight has applied to standard PSO.

Simulation

Particle swarm optimization Parameters values are defined as: C1=0.5, C2 = 0.5, χ = 0.75 and for each iterations inertia weight values change from 1.2 to 0.1. 50 sensors are deployed in the area of 100×100 units arbitrarily over uniform distribution as shown in Fig1 each sensor is having ranging capacity is equal to 20 units and have 4 anchors are deployed, which are located in distinct location.This is assured to design the connectivity region for every sensor as it shown in Fig2. DV distance method is proposed to get the estimated distances of an anchor node to unknown node. Estimated and exactpositionssaparation are generated by all the methods are used find the performance have shown in Fig3 to Fig5 for total 50 sensors.Performance of error minimization in position by PSO has shown in Fig.6.Minimum and maximum error in X and in Y coordinate along with radial minimum and maximum separation among exact and estimated location is also available in Table1.

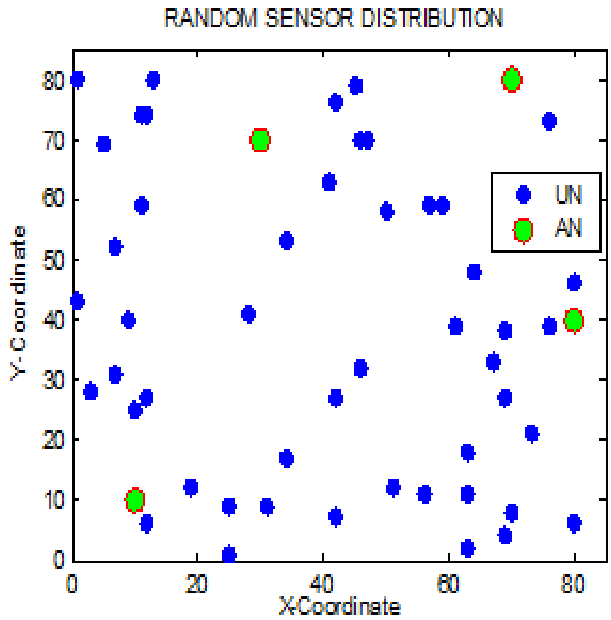

Fig 1. sensors distributed with uniform random distribution

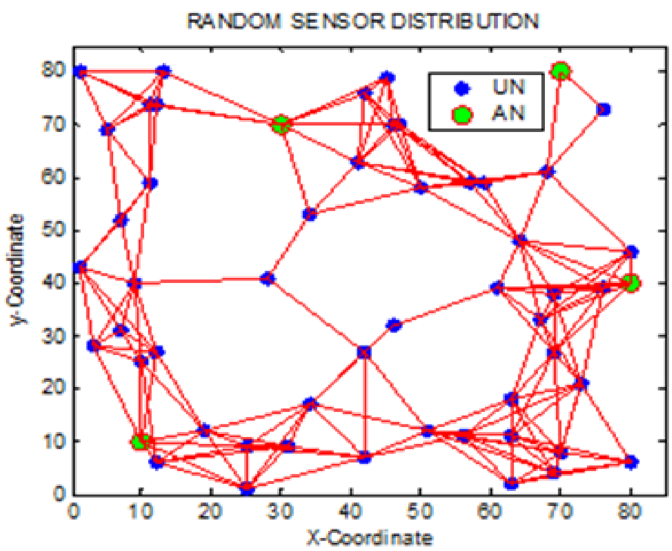

Fig2:sensing range based sensors connectivity

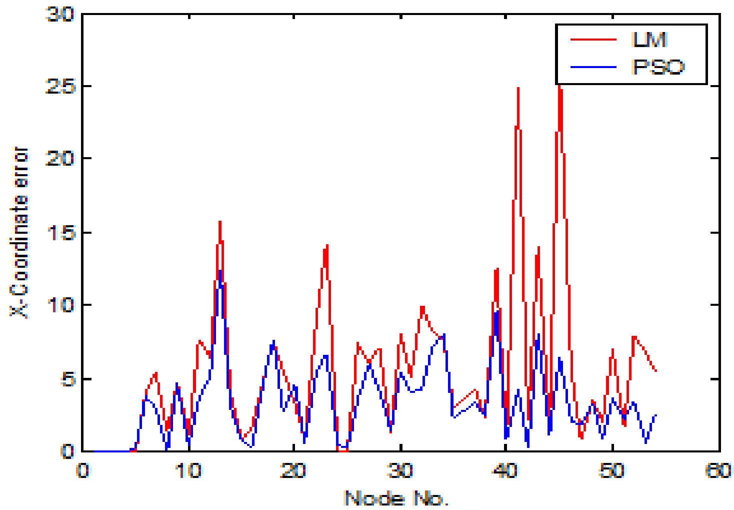

Fig3: X-coordinate absolute error in result shown for position estimation by LM and DWPSO.

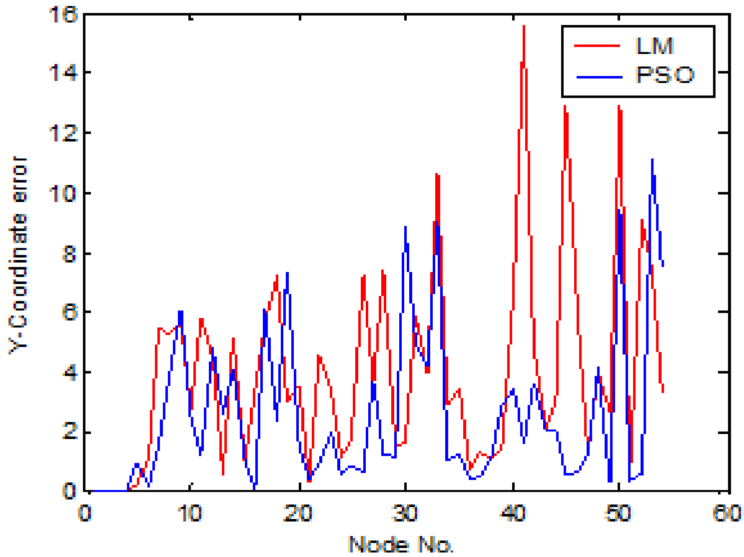

Fig4:Y-coordinate absolute error in result shown for position estimation by LM and DWPSO.

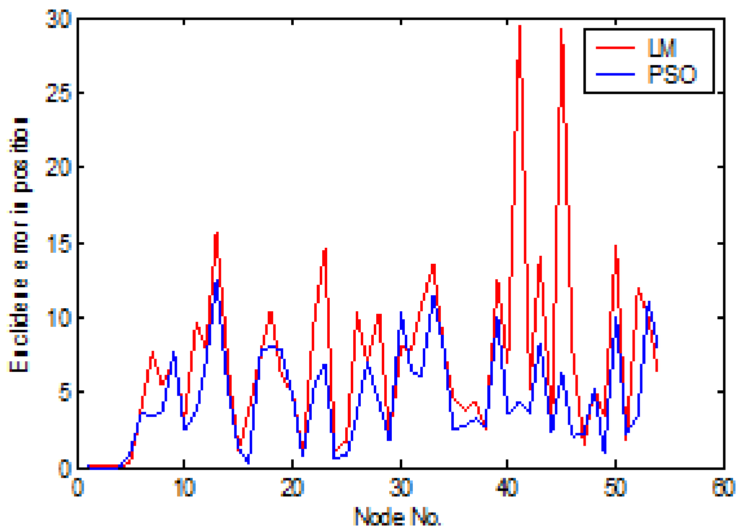

Fig5: Radial error in result shown for position estimation by LM and PSO.

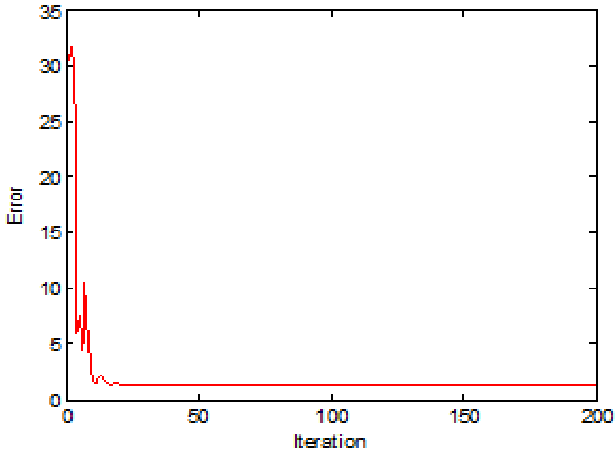

Fig6: Position error minimization for one sensor by AWPSO

Table 1. Minimum and maximum error in position error for position estimation.

Error	LM	PSO
X-Min	0.5329E-14	0
Y-Min	**0**	**0**
Radial-Min	**0.7105** E-14	**0**
X-Max	26.3081	12.2908
Y-Max	15.5141	11.1223
Radial-Max	29.3387	12.5693

IV. Conclusion

This paper discussed about hybrid optimized method using DWPSO and LM algorithm to enhance localization in WSN. Reducing the square error of estimated and measured distance between the neighboring anchor node and unknown node can warranty a better localization accuracy in DWPSO compared LM.Simulation results prove that this method provides smaller localization error, higher localization accuracy and better stability performance in PSO.This paper proposes DE algorithm is used along with PSO to obtain the better results. In future hybrid optimized method using PSO and DE algorithm is to be implemeted .

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