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Self-Adaptive Differential Evolution based Localization of Sensors in Wireless Sensor Network

S.R. Sujatha
Research Scholar, Department of Computer Science & Engineering,
Sri Siddhartha Institute of Technology [SSIT], Tumakuru-572105, Karnataka, India.

Orcid Id: 0000-0001-8593-7895

Dr. M. Siddappa
Professor and Head, Dept. of Computer Science & Engineering,
Sri Siddhartha Institute of Technology, Tumkur-572105, Karnataka, India.

Orcid Id: 0000-0003-0418-9296

Abstract

Wireless sensor network has shown potential in various applications among them monitoring applications have their own importance. In monitoring applications without knowing the position of sensors it is not possible to think about success of purpose. Accuracy in position in many application can be very critical hence it is necessary that position estimation method should have capability to be closer to actual position as much as possible. In this paper heuristic approaches, dynamic weight based particle swarm optimization and self-adaptive differential evolution, have applied for three dimensional mining application which has three dimensional position of sensors. Comparative performance analysis have made against each other in terms of accuracy in target estimation.

Keywords: Wireless sensor network, self-adaptive differential evolution, dynamic weight based particle swarm optimization.

INTRODUCTION

Monitoring applications describe a significant class of applications used in WSN. In these applications the network observes the event occurrences (phenomena) by recognizing different physical properties, such as temperature, ambient light humidity, movement, pressure, and presence (for target tracking). In such circumstances the position data of both nodes and phenomena is typically necessary for tracking and association purposes. In this object we address the localization problem from the perspective of WSN .In wireless sensor networks (WSNs) localization is a one of the fundamental issue for many applications. These features contain the identification and association of collected data, query and managing of nodes localized in a determined area, node addressing, coverage and nodes density evaluation, generation of energy map, topographical routing, object tracing, and other algorithms. The significance of localization data ascends from numerous factors, some of which are correlated only to WSNs. Since sensor networks may be organized in unreachable environments or disaster assistance operations, the location of sensor nodes may not be scheduled. These are all the features make localization method is a one of the key technology for the process and development of WSNs.

OBJECTIVE OF THE WORK

1. Formulate new localization algorithm for identification of sensors.
2. Self-adaption of parameters in differential evolution has applied for better position accuracy and solution reliability.
3. To design an algorithm using self adaptive differential evolution based localization technique.

RELATED WORK

In wireless sensor network localization is one of the key techniques, hence various research have given in past. To estimate the location of sensor nodes mainly two models are used, SVMs-based Localization and CART-based localization has presented in [1].For the duration of the training procedure, input of the models are the reference nodes of the RSS and position information is viewed as the output of two models. Decision trees of CART and support vector machines are used to evaluate the position of blindfolded nodes. In [2] complete review of challenges related with localization: in non-line-of-sight, in energy-constrained network, node assortment standards for localization, cooperative node localization, forecasting the sensor node to improve the tradeoff among energy consumption and localization performance, and for heterogeneous network different localization algorithms are presented. In [3], authors have projected maximum likelihood estimation method to find the location of the unknown node with a constraints in WSN. Three different methods have applied:

1. Measure the distance between node and RSS.
2. Series of positive and negative constrains are combined to build the modeling using the maximum likelihood estimation.
3. To find the optimal position PSO method is employed.

Currently node localization algorithm were focused on the how to place and choose reference nodes has a great influence on the positioning accuracy. In [4] proposed a theorem, which gives the correlation between whether the node can be placed and the placement of reference nodes, then the different algorithm for reference nodes placement was designed. In [5] by using RSS measurement node localization problem in large-scale WSN have been proposed by this authors. In [6] the combinations of information transmission, environment monitoring and emergency localization scenarios has proposed. In[7] indoor localization offerings a better challenges due to occurrences of more severe transmission performances depending on the constraints of the environment has proposed. In [8] Artificial Neural Network (ANN) presents a technique of adaptive processing of location specific non-linear indoor signal propagations are proposed. A general way of attaining WSN localization is through measurements and assessment of Received Signal Strength (RSS) standards of the signal conveyed by target mobile nodes are used to increase its accuracy, for that different localization algorithms are proposed in [9].Three different approaches of ANN family for indoor localization schemes are evaluated in [10]. [11] has proposed a WSN range-free localization algorithm that is tough against the anisotropic signal attenuation induced by shadowing, fading, interference, Popular heuristic algorithms in estimating the location of sensor nodes about accuracy has proposed in[12].In [13] to improve the localization accuracy the combination of regression tree and classification of localization algorithms are proposed. Localization algorithm based on three-dimensional space has proposed in [14].The dynamic adjustment scheme has been applied in the localization algorithm to combat the measurements error in the ranging. The process of localization can be defined as the estimation of nodes position with respect some references which may be absolute or relative. Frame of reference is fundamental to how the WSN performs at executing its functions has discussed in [15]. By using the measurements of the received signal strength (RSS), two closed-form none-ambiguous estimators are proposed to geometrically locate the source position under the shadowing noise in the wireless channel. As one of the important methods in wireless sensor networks (WSN), localization technique has been a research hot issue and essential purpose in most wireless applications to stimulate high localization accuracy and efficiency, different localization algorithm are proposed. [16] Has deliberated the limitation of certain typical works on localization, and suggests a hybrid localization procedure combined with estimated point in distance vector-hop (DV-HOP) and triangle (APIT).

Localization as an Optimization Model

It is possible to model the problem of localization as the optimization problem in terms of system of equalities as defined in (1) assuming there are number of nodes and beacons.

$$\| N_i – B_k \|2^2 = d_{ik}^2 \qquad (1)$$

In Eq. (1) parameters variables B_k are the co-ordinate value of k^{th} beacons and Ni is the coordinate of i^{th} nodes available in the network. d_{ik} is the radial distance between the sensor node and beacon. With this model it is possible to consider the localization system of sensor network as the minimization of error between estimated distance and actual distance between sensors and beacons. Ideally it should be equal to zero and objective can be defined as minimize the function as given by Eq.2.

$$\text{Min} \sum | (\sqrt{} (N_i - B_k)^2) - d_{ik} |, \forall\ i, k \qquad (2)$$

Technically the number of beacons should be more than 2 and developed system of equality generates the nonconvex and non-smooth characteristic of landscape .The complexity category of this problem is NP-hard.

Differential Evolution

To solve the global optimization problems DE as one of the tough entity in evolutionary computation, this algorithm contains D-dimensional vector of NP individuals. To generate the donor vector of dimension D, DE employs mutations during each generation for each vector. There are many policies exist to describe the donor vector. In this work, policies called DE/rand/1 as defined in Eq. (3) has taken. To design a trial vector crossover operator under probabilistic environment has applied as shown in Eq. (4). CR is a crossover control parameter or factor within the range [0, 1] and presents the probability of creating parameters for a trial vector from the mutant vector. Index jrand is a randomly chosen integer within the range [1, NP]. Then a greedy selection operation selects between the target and corresponding trial vectors to choose vectors for the next generation as according to Eq. (5). Eq (6) and Eq (7) gives the self-adapting control parameter mechanism exist which take control of variation on crossover constant CR, weighting factor F. The capacities jrand, jϵ {1, 2, 3, and 4} signifies uniform arbitrary standards in the range [0, 1].To adjust the control parameters F and CR, τ1 and τ2 probabilities are used respectively. 0.1, 0.1, 0.1, 0.9 are fixed values for Constants τ1, τ2, Fl, Fu respectively. The control parameter values are found earlier the mutation process is completed.

$$V_i^{(G)} = A_{r_1}^{(G)} + F \times \left(A_{r_2}^{(G)} - A_{r_3}^{(G)}\right) \qquad (3)$$

$$u_{ij}^{(G)} = \begin{cases} v_{ij}^{(G)} & if\ rand(0,1) \le CR \quad or \quad j = j_{rand} \\ x_{ij}^{(G)} & otherwise \end{cases} \qquad (4)$$

$$x_{ij}^{(G)} = \begin{cases} u_i^{(G)} & if\ f\left(u_i^{(G)}\right) \le f\left(x_{ij}^{(G)}\right) \\ x_i^{(G)} & otherwise \end{cases} \qquad (5)$$

$$F_i^{(G+1)} = \begin{cases} F_l + rand_1 \times F_u & if \quad rand_2 < \beta 1 \\ F_i^{(G)} & otherwise \end{cases} \qquad (6)$$

$$CR_i^{(G+1)} = \begin{cases} rand_3 & if \quad rand_4 < \beta 2 \\ CR_i^{(G)} & otherwise \end{cases} \qquad (7)$$

Self- Adaptive Differential Evaluation Algorithm

1: choice Np individuals $\vec{x}_{m,n}$ randomly

2: For m=1 to Np let $f_m = f(\vec{x}_{m,n})$

3: If Np is even then let $k = N_p/2$ else $k = (N_p + 1)/2$

4: while (convergence criterion not yet met) do steps 5 to 15

5: For m=1 to Np do steps 6, 7

6: For J=i+1 to Np do steps 7

7: If $f_j > f_m$ then swap $\vec{x}_{m,n}, \vec{x}_{j,n}$ and swap f_j, f_m

8: For m=1 to k do steps 9 to 14

9: select three different random indexes r_0, r_1 *and* r_2 between 1 to Np $m \neq r_0 \neq r_1 \neq r_2$.

10: Let $\vec{V}_{m,n} = \vec{X}_{r0,n} + F(\vec{X}_{r1,n} - \vec{X}_{r2,n})$

11: For j=1 to n do steps 12 to 13

12: select randomly r_j variable $(0 \leq r_j < 1)$ and j_{rand} index $(1 \leq j_{rand} \leq l)$

13: If $r_j \leq C_r$ or $j = j_{rand}$ then $u_{j,m,n} = V_{j,m,n}$ else $u_{j,m,n} = X_{j,m,n}$

14: If $f(\vec{U}_{m,n}) \leq f_m$ then $\vec{X}_{m,n+1} = \vec{U}_{j,n}$; $f_m = f(\vec{U}_{m,n})$ else $\vec{X}_{m,n+1} = \vec{X}_{m,n}$

15: For m=l+1 to Np let $\vec{X}_{m,n+1} = m_{i,n}$

Localization of sensor in Mining

To solve the localization problem a practical data set which has taken from a coal mine company. There were number of electronic equipment have been distributed and the need was to estimate their position and the difficulties are manual surveying is not possible because of mine structure. Hence an automated solution needed which could deliver the position more accurately. One possible solution seems like GPS, but under mine, its performance degraded because of irregularity of depth and visibility. Radio beacons can be applied to measure the estimated distance among equipment in mine is the other alternative solution. To evaluate their location, there are eights beacons and three target locations have considered. Exact distance along with distance with error together have shown in Table 1 and in Table 2. Experimentations have given to see the performance of dynamic weight based PSO (DWPSO) and proposed self-adaptive differential evolution (SADDE) in both cases. To estimate the every target position independent trails have given in both algorithms. In PSO ,dynamic weight have applied ,which changed from high value 1.2 to low value 0.1 with increase of iterations. This is justified because in the beginning there is need of larger jump while as solution move near to optimality search step should be small. The other parameters social constant and cognitive constant value have taken 0.5(C1= C2 = 0.5), while constriction factor value, χ is equal to 0.75. Obtained position for all the three targets along with error has shown in Table 3. Convergence characteristic corresponding to each target has shown in Fig1 to Fig.3.

EXPERIMENTAL RESULTS

Table 1: Position of beacons

BEACON	X	Y	Z
B1	475061	1096301	4671
B2	481501	1094901	4693
B3	482231	1088431	4830
B4	478051	1087811	4774
B5	471431	1088581	4753
B6	468721	1091241	4802
B7	467401	1093981	4704
B8	468731	1097341	4748

Table 2: Errors in position of beacons

Error distance	
r1	-0.457891
r2	0.173051
r3	0.316930
r4	-0.191204
r5	0.468338
r6	0.141140
r7	0.324658
r8	-0.390461

Table 3: Position estimated in X, Y, Z direction

Co-ordinates	X	Y	Z	Distance error
Target:1	**480000**	**1093000**	**4668**	
1.DWPSO	480000	10930018.16	4777.77	109.7
2.SADDE	480000	1093000.13	4663.9	4.08

Co-ordinates	X	Y	Z	Distance error
Target:2	480000	1093000	4525	
1DWPSO	480000.7	1093003.9	4801.1	276.1
2SADDE	480000.2	1093000.17	4523.4	1.51

Co-ordinates	X	Y	Z	Distance error
Target:3	**480000**	**1095500**	**4525**	
1.DWPSO	479999.9	1095505.8	4729.5	204.5
2.SADDE	479999.9	1095500.3	4526.3	1.33

TARGET 1

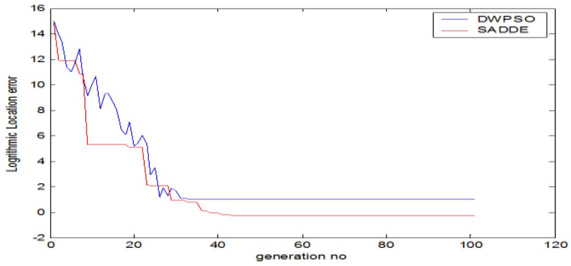

Figure 1: Error characteristic in locating the position of target 1

TARGET2

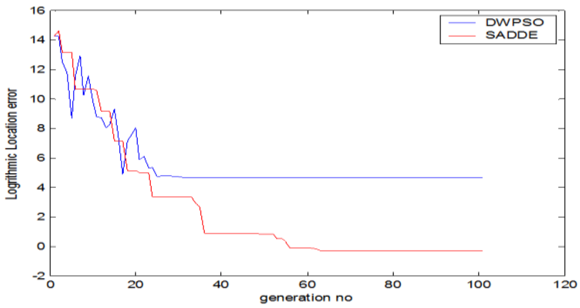

Figure 2: Error characteristic in locating the position of target 2

TARGET3

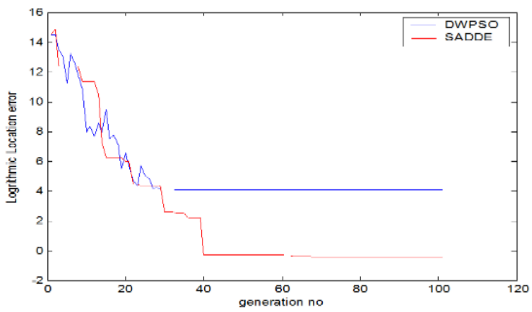

Figure 3: Error characteristic in locating the position of target 3

Whole experiment setup has designed in MATLAB environment. For each target position estimation 100 iterations have allowed and error has estimated as estimated by Eq.1.Logrithmic scale has applied in Fig.1 to Fig.3 to see the clear differences between performances of DWPSO and SADDE, occurred at the later stage of iterations. It is clear that there is very less error occurred in estimation of position by SADDE in compare to DWPSO. There is more fluctuation is also observed in performances of DWPSO which indicate trends of improvement is not very regular in DWPSO while in case of SADDE ,almost there is decreasing tendency with iterations.

CONCLUSION

In wireless sensor network one of the important key techniques is the localization. Target/source localization and node self-localization methods are the two different classification in location estimation. In this research, we present localization in non-line-of-sight condition based application in mining. Computational simplicity is the one of the main advantage of PSO in compare to other natural computing method, but parameters tuning are difficult task and there is no universal value exist hence. It is also true that there is no very effective exploration operator available in result of suboptimal convergence. To achieve the global minima in position accuracy a self-adaptive differential evolution (SADDE) has been proposed. Proposed method has adaptiveness in involved parameters which changes itself with time of solution progress. Proposed method has shown high accuracy in localization of targets in compare to dynamic weight based particle swarm optimization not only that there is faster convergence also achieved.

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