GbLN-PSO Algorithm for Indoor Localization in Wireless Sensor Network

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Abstract. Localization is one of the issue in Wireless Sensor Network (WSN). The problem is the estimation error in the localization of the node. In this paper, we propose an indoor localization in WSN based on Global best Local Neighbourhood Particle Swarm Optimization (GbLN-PSO) algorithm. Three anchors are used as the distance measurement for each unknown node to be localized. A comparison of the performances of PSO and GbLN-PSO in terms of localization error (accuracy) and computation time is presenting using simulation in Matlab. The result shows that GbLN-PSO improved the accuracy approximately by 0.01% and reduced the computational time by 86.02% compared to PSO technique.

1. Introduction

Wireless Sensor Network raised quickly in distinctive area to monitor an application [1]. Two significant parts in WSN are unknown node and anchor. Unknown node has no information of their location, while anchor node having the information of location. To know the node position, each unknown node must have a process of estimation the location known as localization [2]. Localization is an important matter in area of WSN because the sensed data that has been detected by the node is purposeless if the information of the node position is unknown. Sensor nodes that have their location will conduct to increase the efficiency in power saving, routing and efficiency in collecting the source of the sensed information. The traditional technique used can solved the localization problem, but the estimated location is not accurate. Accuracy shows the reading how closed the truth node location and estimated node location. Knowing an unknown node position with high accuracy will lead the information to be delivered efficiency. The main problem in most current localization techniques is to achieve the high accuracy. The accuracy can be determined by calculating the percentage of localization error. The higher localization error gained; the lower accuracy will be achieved and vice versa. If the node position is wrongly estimated, the accuracy of the node will be reduced [3].

In the localization process, there are two types which are outdoor and indoor. The famous outdoor localization tool is Global Positioning System (GPS). GPS works by gaining minimum three satellites signals from the telecommunication station and through the process of localization. The outdoor localization has been used widely for the industrial applications of transportation, handling of the forest fires, logistical application and etc. [4]. Meanwhile the indoor localization is utilized to provide exact location of unknown node for indoor environment such as hospital, universities, shopping complex and etc. The vital challenges for indoor localization are need to face many obstacles that blocked the transfer...
Tools of localization like an installation of GPS into sensor node, it may help to estimate the location. However, GPS still not a decent choice because the installation cost of the GPS at each of the node is super costly. Besides that, the node’s lifetime will be shorted because GPS consume more power consumption from the battery to receives a signal and execute the localization process. In additional, GPS signal from satellites is powerless to pass through the buildings and it makes GPS tool is not a best choice for indoor localization. Because of that, different localization technique is required to take the place of the GPS for indoor localization [5].

Ranging phase is the approach that can be used in measuring the range between nodes. The ranging process will take the measurement angle or the calculation of the signal so that, it will produce a distance between two nodes. In the ranging phase, there are two versions which are range free and range based. There are four techniques that can be used in range based which are the Angle of Arrival (AOA), Time Distance of Arrival (TDOA), Time of Arrival (TOA) and Receive Signal Strength Indicator (RSSI) [6]. Besides that, there are five techniques in range free which are Approximate Point in Triangle (APIT), Hop-Count-Based localization, Multi-Hop, Centroid and Gradient [7]. The hybrid localization technique is determining as combination of two or more different techniques such as combine RSSI and AOA [8].

The rest of this paper are arranged as followed, the details about PSO and Variants PSO has been described in Section 2. Section 3 will be discussed about the proposed algorithm (GbLN-PSO), and Section 4 is the experiment setup. Section 5 is result and discussion, Section 6 will present the conclusion and potential area of improvement for research in future.

2. Related Works
At the initial of PSO study, many researchers are focussing on solving the optimization problems for a static environment. Wachowiak et al. address the constrained Economic Load Dispatch (ELD) problems and the author applied an Adaptive particle swarm optimization method to solve the problems [9]. Furthermore, Centripetal Accelerated Particle Swarm Optimization (CAPSO) has been introduced by Tareq et al. to increase the performance of particle in PSO algorithm by running the experiment of accuracy, convergence speed and global optimality searching algorithm [10]. This experiment was running by using real and binary search spaces are considered in the test space environment.

Nowadays, the researcher has made an improvement to the PSO algorithm in order to overcome the problems in dynamic environment. Stojkoska et al. introduced Multidimensional particle swarm optimization in dynamic environments to overcome premature particle convergence problem and speed up the convergence particle to the global optimum method by allowing each particle to converge at a different optimum [11].

Zhang et al., has proposed the distance error from actual location and the estimation location of node, by employing the PSO as the optimization problem [8]. Viet Duc Le et al. has introduced PSO algorithm for distribution of localization in WSN to calculate the location of unknown nodes depends on the position data of anchors [12]. The PSO algorithm work by minimizing the localization error. It will enforce many communications and it can lead to take slowly, exhaustion and congestions of energy.

Different to Kulkarni et al., recommended iterative distribution of node localization using PSO algorithm [13] where the set of Unknown node receives three or many anchors in their communication range and perform PSO algorithm with minimizing the localization error. This method makes each of the nodes unnecessary to transmit their position information to a central node in order to run the localization process. Moreover, all the node will be localized as long as the node in the range of their communication signal. However, using PSO algorithm for localization purposed need to consider the time complexity because higher computation time will influent higher computation energy.
The methods discussed above show that the localization process still have their weaknesses, especially the exploitation and exploration of particles in a search space. The particles are sometimes it does not work out the optimal solution, but its converging near to optimum peak. For that reason, this paper proposed the Global best Local Neighbourhood in Particle Swarm Optimization (GbLN-PSO) algorithm to overcome the problems of the unknown node localization.

3. GbLN-PSO algorithm

3.1. Global best Local Neighbourhood Particle Swarm Optimization

Various of applications using Computational Intelligence in WSN can be found such as Defence Advanced Research Projects Agency (DARPA) for military, Automated Local Evaluation in Real Time (ALERT) for environmental, and etc. PSO have been implement in various of filed such as object tracking, Wireless Network and detection problem.

In traditional PSO, each of the particles has the distance from the target location and it is represented as fitness or objective function for that problem. Every particle possesses its own Pbest (particle best as the best location itself), and in between all the particles, there will be a particle whose located closed to the target that called as Gbest (global best as the best among the particle location). In PSO algorithm, a set of particles will move quicker toward the way of the particle that have lowest value objective function. In each iteration, each particle’s position and velocity are being updated and keep searching a new location. It is iterating continuously until the condition is satisfied.

In Equation (1), $d_i$ is the actual distance which is Euclidean distance. According to (1), the location of unknown nodes represents as $(x, y)$. While $(x_i, y_i)$ is represented as the position of $i$th anchor. The algorithm will find the coordinates of $(x, y)$ by minimizing the fitness function. Where $f(x, y)$ represents as localization error such as in Equation (2) that used to calculate the error between estimated distance and actual distance of the nodes. After the estimation node are calculated, then the value will be used to generate the fitness function shown in Equation (3):

$$d_i = \sqrt{(x-x_i)^2 + (y-y_i)^2}$$

$$f(x, y) = \frac{1}{M} \sum_{i=1}^{M} \sqrt{(x-x_i)^2 + (y-y_i)^2 - d_i}$$

$$f_i(x, y) = d_i - \sqrt{(x-x_i)^2 + (y-y_i)^2}$$

$(\hat{x}, \hat{y})$ is the estimated coordinate of unknown node, $(x_i, y_i)$ where $(i = 1, 2, ..., M)$ is the actual coordinate of the $i$th anchor node and the unknown node, where $f_i(x, y)$ is the error value between measured and estimated distance of the $i$th anchor node and unknown node. $d_i$ is measured distance between anchor and unknown node as shown in Equation (1). After the ranging phase is completed, the estimation phase will take place the initializing the location of the particles. Distribution of the particles in the area of the network size or search space.
The pseudocode of GbLN-PSO is given in Figure 1. In GbLN-PSO, the basic PSO algorithm has been added with another processes as shown in line 18 to 27 where every particle is compulsory to generate a small population of their Neighbourhoods as a virtual particle, and distributed along the location of the particle move to new location. The Neighbourhood particle generates using the Equation (4) as shown below:

\[ I'_i = N(-a, a) + I_i \]  \hspace{1cm} (4)

Where
\[ a = x_i - x_{i-1} \]

\( N(-a,a) \) is the random number to generate the neighbourhood particle. Then, the neighbourhood particle will calculate fitness and local best of every of particle. If the fitness of neighbourhood is better than local best particle \( f_l < f_i \), the fitness neighbourhood and the location particle will replace the local best and fitness value of local best, \( f_i = f'_i \) and \( I_i = I'_i \) respectively. Process of evaluating local best neighbourhood particles will carry out to evaluate global best. From Zalili et al. [21], this idea made particle more comprehensive in the searching process. The neighbourhood particle will make sure the particle not only focus on certain area. This process also controls the movement of particle to being converge early and let the particle to search along the same direction of global best result.

3.2. Communication Model

In this paper, Received Signal Strength Indication (RSSI) is implement to determine the distance from the anchor to unknown node by using as in Equation (5). The RSSI technique provides the mechanism to calculate the distance between sensor nodes. An unknown node calculates the distances from each of the anchors when it received signals from three anchors. From Equation (5), \( P \) is the power that received at reference distance, \( D_0 \), \( n \) is the path loss index, \( D \) is the nodes distance and \( X \sigma \) is the noise parameter with zero mean Gaussian random variable.

\[ RSSI = P - 10\eta \times \left( \log \frac{D}{D_0} \right) + X \sigma \]  \hspace{1cm} (5)
$g$ = global best

$f_g$ = fitness value of $g$

$l_i$ = local best of particle $i$

$f_i$ = fitness value of $l_i$

$l_i'$ = local best neighbourhood particle $i$

$f_i'$ = fitness value of $l_i'$

$w$ = weight

$c$ = constant value

$r$ = random value

$S$ = search space

$R$ = size of network

Step 1: Initialization location of the particles

1. $x_i \sim N(0,1) \ast R$

Step 2: Evaluation of the population

2. For $n = 1:N$

3. Calculate $f_i \forall i$ in Equation (3)

4. If ($t = 1$)

5. For $i = 1:I$

6. $l_i = x_i$

7. $f_i' = f_i$

8. End loop

9. Else

10. For $j = 1:J$

11. $l_j' = N(-\alpha, \alpha) + l_j$

12. Calculate $f_i'$

13. If ($f_i' < f_i$) then

14. $f_i = f_i'$

15. $l_i = l_i'$

16. End if

17. End loop

18. For $j = 1:J$

19. $l_j' = N(-\alpha, \alpha) + l_j$

20. Calculate $f_i'$

21. If ($f_i' < f_i$) then

22. $f_i = f_i'$

23. $l_i = l_i'$

24. End if

25. End loop

26. For $i = 1:I$

27. If ($f_g < f_i$) then

28. $f_g = f_i$

29. $g = l_i$

30. End if

31. End loop

Step 3: Updating of the particles

32. For $i = 1:I$

33. $V_i = wV_i + c_1r_1(l_i - x_i) + c_2r_2(g - x_i)$

34. $x_i = V_i + x_i$

35. End loop

36. End loop

37. End loop

Figure 1 GbLN-PSO Algorithm

4. Experiment Setup

In order to evaluate the GbLN-PSO algorithm performance in WSN, we simulated the experiment using Matlab 2014 software and Intel(R) Core(TM) i7-2600 CPU @ 3.40 GHz. The parameters that we are applied for localization as shown in Table I. The parameters for PSO and GbLN-PSO is listed in Table II and the number of particle both PSO and GbLN-PSO show in Table III. In this experiment, the simulation has been run for 40 unknown nodes based on [28] and [27]. The weight and coefficient values is selected after the tuning parameter process is conducted.

| Parameter               | Values |
|-------------------------|--------|
| Network Size            | 100 × 100 m² |
| Anchors Node            | 3      |
| Unknown Nodes           | 40     |
Table 2. Simulation Parameter for PSO and GbLN-PSO

| Parameter          | Values            |
|--------------------|-------------------|
| Maximum Iteration  | 50                |
| Weight             | 0.4               |
| Coefficient        | 1.3               |
| Random Number      | [0,1]             |
| Particle Position  | Xmin=0, Xmax=100  |

Table 3. Number of Particle for PSO and GbLN-PSO

| Algorithm  | Number of Particle | Neighbor Particle | Total Particle |
|------------|--------------------|-------------------|----------------|
| PSO        | 20                 | -                 | 20             |
| GbLN-PSO   | 5                  | 3                 | 20             |

The average of the localization error $E$, calculated using Equation (6), which is delineate as the total error between truth node locations with the estimated, $(x,y)$ location. Total error, $f(x,y)$ will be divided by total number of the unknown nodes, $N$.

$$E = \frac{f(x,y)}{N} \quad \text{(6)}$$

5. Result and Discussion

Figure 2 shows the comparison of required iterations number to converge on minimum value of unknown node. The PSO algorithms have applied 20 particles and GbLN-PSO algorithm applied 5 particles and 3 neighbourhoods respectively. In GbLN-PSO algorithm, less particle was applying because of existing of neighbourhood particles help the searching process. The convergence of the particle on PSO is fastest then GbLN-PSO. At the number iteration of 5th PSO have converge. It is different to GbLN-PSO, where the particles have been converging at iteration of 10th. GbLN-PSO able to avoid from being in the local optimum. The faster of convergence make the less exploitation of particle in the search area. Based on convergence result, the neighbourhood particles are distributed at the 6th of iteration. This is because at the 6th iteration, the neighbour particle will through the local search to avoid trapped into local optimal.
In this Figure 2 experiment, computational time is also evaluated to differentiation the attainment of the proposed algorithm. The time taken for computation is depends on how long particle take time to find the target, the number of particles. It is also can supposed that the longer computation time brings much energy consumption. Thus, we run the simulation and determine the value localization error and computation time for further analysis. The details of running experiment as shown in Table 4.

**Table 4. Simulation Parameter for Localization**

| Algorithm     | Average Localization Error, $E_t$ (m) | Computational Time (s) |
|---------------|---------------------------------------|-------------------------|
| PSO           | 0.449675                              | 213.3863                |
| GbLN-PSO      | 0.444158                              | 29.82545                |

From Table 4, PSO algorithm recorded high localization error at 0.449675m compared to GbLN-PSO algorithm is at 0.44960m. This is because GbLN-PSO algorithm has more exploration and exploitation of particle to find the optimum value. GbLN-PSO has an advantage that can avoid the particle from converge early compared to PSO. GbLN-PSO algorithm required less computational time at 29.82545 second compared to PSO which is take 213.3863 second. GbLN-PSO utilized neighbour particles that are scattered in the same iteration of the main particles. This neighbourhood particle features make the particle able to do the exploitation process and with less time taken to complete the process quickly.

In summary, GbLN-PSO able to localized the unknown node coordinates accurately, while PSO do so but with significant high localization error compare to GbLN-PSO. The impact of high localization error makes the accuracy of node position low. The simulation results show that the GbLN-PSO algorithm can minimize the localization error and the computational time also improved significantly compared to PSO. The GbLN-PSO algorithm has great result of the computational time as the time to localized node is decreased, it will save the power consumption. From the experimental result show that GbLN-PSO can achieved lower localization error and lesser computational time. This are two contributions in the unknown node localization in WSN.
6. Conclusion
As the conclusion this paper implemented Global best Local Neighbourhood Particle Swarm Optimization (GbLN-PSO) to solve indoor localization problem in Wireless Sensor Network (WSN). A set of unknown nodes perform localization by estimating the distance from different three anchors. The distance from anchor to unknown node is calculating using Receive Strength Signal Indicator (RSSI). Generally, PSO have converge earlier to find the optimal solution that make PSO trap into the local optimal problem. On the other hands, GbLN-PSO has improved the localization error and computational time. For further research, we suggest to improve the current algorithm (GbLN-PSO) into the mobile node.

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