PSO based Deployment Algorithms in Hybrid Sensor Networks

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Summary
The effectiveness of wireless sensor networks (WSNs) depends on the coverage and target detection probability provided by dynamic deployment, which is supported by the several methods. Particle Swarm Optimization (PSO) algorithm is one these methods, however computation time required is a big bottleneck. This paper proposes three dynamic PSO-based deployment algorithms that reduce the computation time. First algorithm by the name of “PSO-LA” algorithm comprised of PSO algorithm and learning automata. In this algorithm, speed of particles is corrected by using the existing knowledge and the feedback from the actual implementation of the algorithm. Hence in this algorithm mobile nodes move more objectively than PSO and achieve the result with less number of repetitions. To improve performance of this algorithm, second algorithm by the name of “Improved PSO-LA” algorithm is introduced, regulating its movement without an impact from the movement of other mobile nodes and based on the result gained from its previous movement. The first and second algorithms require sensors to move iteratively, eventually reaching the final destination. In the third algorithm by the name of “Improved PSO-LA with logical movement” with the same round-by-round procedure of the second algorithm, sensors calculate their target locations, virtually move there. The real movement only happens at the last round after final destinations are determined. Simulation results show the effectiveness of our proposed algorithms against other common approaches like VF and PSO algorithms.
Key words:
Wireless Sensor Networks, Dynamic Deployment, Particle Swarm Optimization, Learning Automata

1. Introduction

Wireless sensor networks (WSNs) are the key technology for the future world, which are suitable for many applications, such as surveillance, environmental monitoring, especially in target tracking[1]. Coverage and target detection probability are the two most significant factors for the performance of WSNs [2], which are determined by dynamic deployment algorithms [3]. In initial deployment, randomness is often adopted which, however, always does not lead to effective coverage. Recently, much research effort has been dedicated to dynamic deployment algorithms [3,4,5]. Among this the virtual force (VF) algorithm [6] emerges as one of main approaches for dynamic deployment offering outstanding performance for improving the coverage of WSNs.
Many applications demonstrate that the VF algorithm performs well for self-organizing dynamic deployment [6,7,8]. But these experiments are all implemented in the WSNs consisting only of mobile sensor nodes, but WSNs in practice consist of mobile sensor nodes and stationary sensor nodes to reduce the cost and energy consumption [9]. In this situation, the performance of the VF algorithm will be deteriorated because the force exerted by stationary sensor nodes will hinder the movements of mobile sensor nodes. To solve this problem, Wang [10] proposed a deployment strategy based on parallel particle swarm optimization (PPSO) using the effective coverage performance taken as criterion, where the parallel mechanism is used for saving computation time. However, since the computation complexity of particle swarm optimization (PSO) will increase exponentially as the dimensionality of the search space increases, the computation time is a big bottleneck in PSO.
This paper presents three PSO based algorithms. “PSO-LA” is introduced, based on which the speed of particles is corrected by using the existing knowledge and the feedback from the actual implementation of the algorithm. In “Improved PSO-LA” each mobile sensor equipped with learning automata, regulating its movement without an impact from the movement of other mobiles and based on the result from previous movement. To overcome repetition and zigzag movement, “Improved PSO-LA with logical movement” is introduced, in which mobile sensors move only once to their destination.
The organization of the paper is as follows. Section 2 introduce the system model and prior assumptions required by dynamic deployment in WSNs. Section 3 introduce the details of propose algorithms. Simulation experiments in several typical scenarios have been carried out and are

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described in section 4. Finally, Section 5 concludes this paper.

2. System model and Prior Assumptions

Wireless sensor networks always consist of many stationary and mobile sensor nodes. Because there is no a priori knowledge of terrain or obstacles in the area of interest, all sensor nodes are randomly scattered in the sensing field while initializing.

Without loss of generality, we assume that: (1) WSNs consist of a super node which acts as the sink node and processing center for implementing the proposed algorithms [11]; (2) mobile sensor nodes can move to the scheduled position exactly; (3) each sensor knows its location by some mechanism such as Global Positioning System (GPS).

3. Proposed Algorithms

3.1 PSO-LA algorithm

In the standard PSO algorithm, the responsibility to strike a balance between global and local search is with the median coefficient. This coefficient determines how much of the particle's current speed was used in determining its speed in the next phase. However, in [12], a new algorithm has been recommended which uses learning automata to regulate the method of searching for particles. It is the learning automata which determines in each step that particles continue in their current route or follow the best particles found so far. Using the learning automata has two advantages: First, the existing knowledge can be used to determine the trend of changes in the medial weight, and second, the trend can be corrected in the actual environment by using the feedback from implementation of algorithm.

Here, a new algorithm is introduced by the name of PSO-LA for improving the performance of dynamic deployment. In this algorithm, it is assumed that the mobile sensors are equipped with learning automata (LA). The used LA has two actions which are “Follow the best” and “Continue your way”.

Until the desired goal is met or maximum number of iterations is done, the following steps should be repeated:

(i) LA selects one of its actions based on its probability vectors.

(ii) Based on the selected action, the method of velocity updating for particles is selected and then the particles update their velocity and position.

(iii) According to particles' updating results a reinforcement signal is generated which will be used to update the probability vectors of learning automaton.

The selected action of LA in any iteration specifies the velocity updating method of particles for that iteration. Selecting “Follow the best” action means that just following the best self experience and best team experience has effect on the velocity of the particle in the next iteration and the current particle’s velocity is ignored. In this case, the velocity and position update of the particles is done according to equation (1) and (2) respectively. If the “Continue your way” action is selected, the new velocity of the particle will be equal to its current velocity.

$$v_{ij}(t+1) = c_1 \times r_{1i}(t) \times (pbest_{ij}(t) - position_{ij}(t)) + c_2 \times r_{2i}(t) \times (gbest_{ij}(t) - position_{ij}(t)) \quad (1)$$

$$Position_{ij}(t+1) = position_{ij}(t) + v_{ij}(t+1) \quad (2)$$

Where $position_{ij}(t)$ represent the position of ith particle in the jth dimension at time t. $pbest_{ij}(t)$ is the local best position of ith particle in jth dimension and $gbest_{ij}(t)$ is the global best position. The fitness of the position vector is presented by the effective coverage area. $r_{1i}(t)$ and $r_{2i}(t)$ are two separate random function in the range[0,1]. c_1, c_2 are learning factors. The velocity of particle in each dimension is limited to the *Vmax[i]* which *i* is the index of dimension. The formal description of the PSO-LA algorithm is shown in Figure 1.

```
Initialize the LA
Analyze the effective coverage area formed by stationary nodes
For each Mobile sensor
      Create and initialize an n-dimensional PSO
End For
Do
       The LA selects an action ac
       For each particle     I ε [1….s]
               Evaluate the effective coverage area    fp
               /* updating particle’s best fitness value so far*/
             If    fp is better than pBest
                     Set current value as the new pBest
End For
       /*updating    population’s best fitness value so far)*/
     Set gBest to the best fitness value of all particles
    For each particle
          if   ac is “follow the best”
              Calculate particle velocity according equation (1)
              Else
                  Set particle velocity equal to its current velocity
         End if
      Update particle position according equation (2)
   End For
While stopping condition is satisfied (maximum iterations OR
                  Sufficiency good fitness)
```

Fig. 1 Pseudo code of the PSO-LA based dynamic deployment algorithm for WSNs.

As a matter of the fact, the selection of the “Follow the best” action causes a local search around the best particle and selection of “Continue your way” action has the effect of doing global search and discovering new unknown parts of the search space. The used LA is responsible for learning probability distribution and balancing between local and global search. Evaluating the selected action is done by comparing each particle's new position with its old position. If a specific percent of population (C_{imp}) are improved, the selected action will be evaluated as positive and in the other cases it will be evaluated as a negative action. C_{imp} is a parameter of the proposed algorithm that should be configured based on the problem and used LA.

Given that in this algorithm, the speed of particles is corrected by using the existing knowledge with the less number of repetitions, this algorithm achieves the result with less number of repetitions and mobile nodes move more objectively. As a result, in this method, there will be less re-location for achieving the desired result and therefore, there will be less energy consumption compared to PSO algorithm.

3.2 Improved PSO-LA Algorithm

In Improved PSO-LA Algorithm, a learning automata is allocated to each of the particles. Each learning automata is in fact the core of the particles, which guides its movement within the search space. Allocation of learning automata to each of the particles causes each particle to make decisions for determining the type of its movement without considering the movement of other particles and by using the result of its current movement in the environment. Each learning automata has two actions of "follow the best" and "continue your way". When an automata allocated to a particle chooses the action of "follow the best", it means that the particle, according the equation (1), moves towards the best location met by the group (*gbest*) and best location which has met so far (*pbest*) to move in the search space with the zero weight motion inertia. If the learning automata of each particle select the action of "continue your way", it would mean that the particles is moving within the space at a current velocity and will continue the current way.

The algorithm in this method is as the following:

(i) Particles with initial velocities are randomly deployed in target field.

(ii) A learning automata is allocated to each of the particles.

(iii) The probability vector of selection LA action in each particle is initialized.

(iv) As long as the maximum number of steps are taken or the desired objective is achieved, phases (v) to (x) are repeated:

(v) The LA related to each particle selects one of its actions according to the probability factor of its actions.

(vi) If the LA allocated to ith particle selects "follow the best", the speed of the particles is updated according to formula (1).

(vii) If the LA allocated to the particle selects "continue your way", the speed of the particle will be equal to its previous speed.

(viii) Considering the selection action, the method of updating the speed of the particles is determined and then, particles will update their speed and location.

(ix) If the new location of the particle improves compared to its previous location, the particle will be awarded for the action it selected. Otherwise, the action will be penalized.

$$\beta = \begin{cases} 0 & fitness(X_i(t+1)) \succ fitness(X_i(t)) \\ 1 & otherwise \end{cases} \tag{3}$$

(x) The action selection probability range of the LA is corrected.

This algorithm achieves the result with less number of repetitions and mobile nodes move more objectively. As a result, in this method, there will be less re-location for achieving the desired result and therefore, there will be less energy consumption compared to previous algorithms. In this algorithm, each particle will determine the type of its action in the next phase according to the result of its implementation in the previous phase, thus less energy will be consumed.

3.3 Improved PSO-LA algorithm with Logical Movement

The previous proposed algorithms operate based on PSO. Repetitive and zigzag movements are the main problems in PSO that resulted in long moving distance, high energy consumption and long execution time. To overcome these problems, Improved PSO-LA algorithm with Logical Movement is proposed. The same round-by-round procedure of the Improved PSO-LA Algorithm virtually is considered. The real movement only happens at the last round after final destinations are determined. As a result, no zigzag movement is done. Logical movement method is much more energy-efficient and increases network life time. The number of movement in this method is equal to the number of available sensors in target field.

4. Experimental Results

Proposed Algorithms are implemented in Matlab (Version R2008a). Our objective in conducting this evaluation study is by comparing Virtual Force (VF), PSO and our algorithm giving some insight on choosing suitable algorithm in different situations.

At first, a WSNs including n_s=80 stationary nodes and n_m=20 mobile nodes is simulated. The detection radius of each sensor is r=6m, and their communication range 20m. The sensor nodes are deployed in a square region with area 10000 m2. The parameters for PSO algorithm are set as $c1=c2=c3=1$ and C_{imp} is set to 75. The numbers of used particles in all PSO algorithms are all 10. Each mobile sensor has an initial energy of 3960 J (joule) reserved for movement and the moving energy cost per meter is set to 8.27 J. For calculating the level of energy consumed by each mobile node by one unit, the following mentioned equation can be used [13]:

$$W = \Delta_{move} \times d(a_i, l_j) \qquad (4)$$

Δ_{move} is the energy required to move a sensor one-unit distance (Δ_{move}=8.27), $d(a_i, l_j)$ is the Euclidean distance from a_i's current position and finally l_j is the point which mobile node will move there.

For detailing the comparison of convergence speed, the improvement of effective coverage during the execution of VF, PSO, PSO-LA and Improved PSO-LA algorithms are compared and the results for 100 nodes including 80 stationary and 20 mobile nodes are shown in Figure 2.

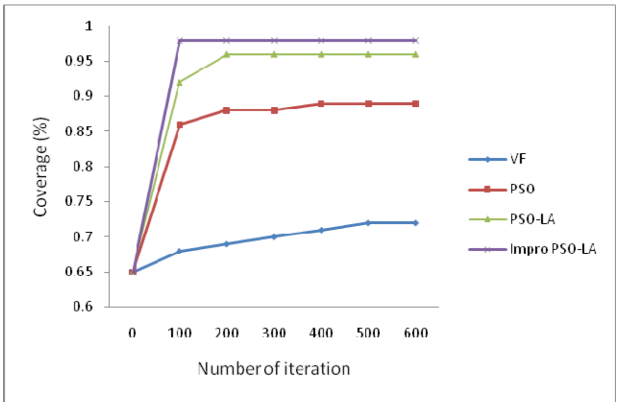

Fig2. The improvement of effective coverage during the execution of the VF, PSO, PSO-LA and Improved PSO-LA

Obviously, Improved PSO-LA can quickly converge to a global optimal with only 15 iteration, while PSO-LA is trapped in suboptimal location in search space with 130 iteration. Without the guidance of learning automata, PSO algorithm improves the effective coverage more slowly than the PSO-LA and Improved PSO-LA algorithms, and it also converges to suboptimal after 350 iterations. Furthermore, VF algorithm is significantly impacted by the virtual force exerted by stationary nodes; this propagation process may take a long time. So the effective coverage area stays around 72% for a long time.

The result shows that the dynamic deployment determined by Improved PSO-LA algorithm can effectively cover most area of region of interest (97.6%).

Between logical movement algorithm and Improved PSO-LA algorithm, logical movement algorithm achieves almost the same coverage as the Improved PSO-LA algorithm, as expected. We can conclude that using logical movement will not affect the achieved coverage.

Figure 3 shows the comparison of the number of movement for different senor densities (80 nodes are stationary and the other are mobile sensor nodes). As shown in the figure, VF algorithm has the largest number of movement because VF makes sensors to reach relatively balanced positions.

As it was mentioned before, the PSO-LA algorithm, in comparison with the VF and PSO algorithms, uses the result of the feedback from the movement of its particles in the actual environment. Therefore, the result is achieved in less number of repetitions and less number of re-located nodes.

In the Improved PSO-LA algorithm, each particle determined the type of its movement in the next phase without considering of the movement of other particles, and only taking into account the result achieve from its own implementation in the previous phase. Therefore, the number of re-locations is less and particles move more objectively.

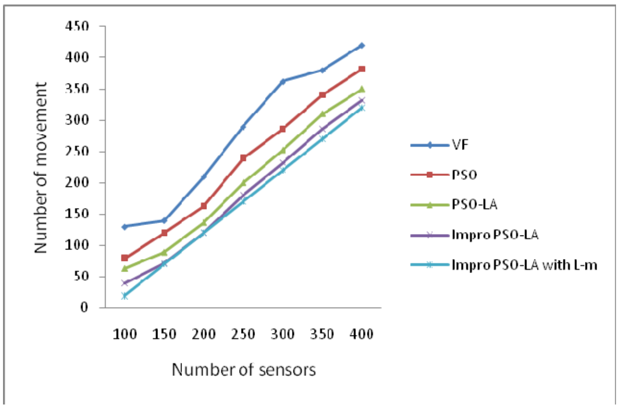

Fig3. A comparison of the number of movement for mobile sensors

In Improved PSO-La with logical movement, we can see that the number of movements is greatly reduced by using logical movement. The sensors have no repetitive movement and move only once to their destination to minimize the sensor movement. Thus the number of movement equals to number of mobile nodes.

Figure 4 and Figure 5 show the Average Moving Distance and Average Energy Consumption for different sensor densities, respectively. As figures illustrate, increasing number of sensors resulted in decreasing average moving distance and average energy consumption in mobile sensors. In the Improved PSO-LA algorithm, because each particle will determine the type of its movement in the next phase according to the result of its own implementation in the previous phase, mobiles move within a shorter distance compared the other three algorithms. From the figures, we can conclude that logical movement algorithm is much more energy-efficient than the other algorithm.

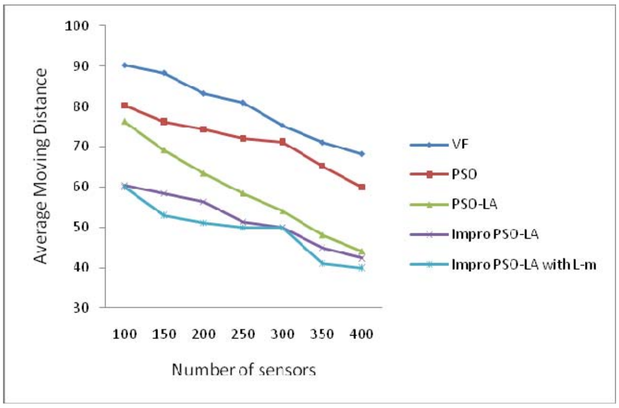

Fig4. Average Moving Distance for Relocated Mobile Sensors

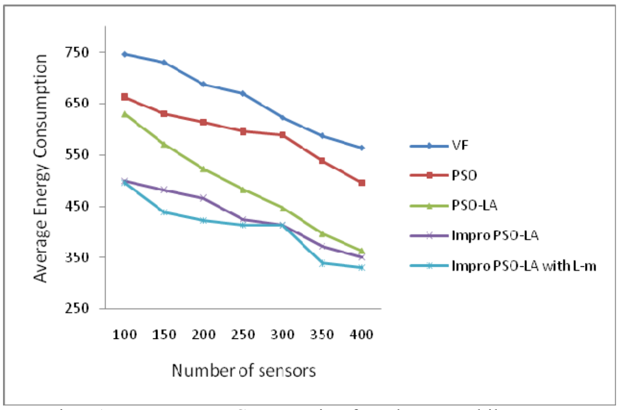

Fig5. Average Energy Consumption for relocate mobile sensors

By studying these four figures, it can be noted that by using the Improved PSO-LA and Improved PSO-LA with Logical movement algorithms, the mobiles have to travel within a shorter distance compared to other three algorithms and therefore, they consume less energy. The PSO-LA algorithm in comparison with PSO and VF algorithms travels within a shorter distance for each mobile, and as the result it has low energy consumption.

4. Conclusions

In this paper three PSO based algorithms for improving the performance of dynamic deployment are proposed. In the PSO-LA algorithm, by using LA, the speed of particles is corrected by using the existing knowledge with the less number of repetitions. As a result, in this method, there will be less re-location for achieving the desired result and therefore, there will be less energy consumption compared to PSO algorithm. In the Improved PSO-LA algorithm, allocation of learning automata to each of the particles causes each particle to make decisions for determining the type of its movement without considering the movement of other particles and by using the result of its current movement in the environment. The logical movement algorithm can significantly reduce mechanical movement of Improved PSO-LA algorithm.

It can be declared that the proposed Improved PSO-LA and Improved PSO-LA with logical movement algorithms have good local and global searching and regional convergence abilities in the procedure of optimization and they can implement the dynamic deployment of hybrid WSNs with mobile and stationary sensors nodes rapidly, effectively and robustly.

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