Lifetime Improvement Using Cluster Head Selection and Base Station Localization in Wireless Sensor Networks

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Abstract

The limited energy supply of wireless sensor networks poses a great challenge for the deployment of wireless sensor nodes. In this paper, a sensor network of nodes with wireless transceiver capabilities and limited energy is considered. Clustering is one of the most efficient techniques to save more energy in these networks. Therefore, the proper selection of the cluster heads plays important role to save the energy of sensor nodes for data transmission in the network. In this paper, we propose an energy efficient data transmission by determining the proper cluster heads in wireless sensor networks. We also obtain the optimal location of the base station according to the cluster heads to prolong the network lifetime. An efficient method is considered based on particle swarm algorithm (PSO) which is a nature inspired swarm intelligence based algorithm, modelled after observing the choreography of a flock of birds, to solve a sensor network optimization problem. In the proposed energy- efficient algorithm, cluster heads distance from the base station and their residual energy of the sensors nodes are important parameters for cluster head selection and base station localization. The simulation results show that our proposed algorithm improves the network lifetime and also more alive sensors are remained in the wireless network compared to the baseline algorithms in different situations.

Keywords: Wireless Sensor Nodes; Network Lifetime; Particle Swarm Algorithm (PSO); Base Station; Cluster Head.

1. Introduction

Nowadays, wireless sensor networks (WSNs) are used in various applications such as military tracking, environmental monitoring, medical diagnosis and habitual monitoring, etc. The significant role of the sensor nodes in these networks include data gathering from the environment and send it to the base station (BS) to make a final decision about the status of the environment. However, energy consumption of the sensor nodes is one of the main concerns in wireless sensor networks. Clustering is one of the most efficient techniques to save energy in these networks. In this technique, sensor nodes transmit their data to some leader nodes called cluster heads (CHs). CHs send aggregated data to BS in one-hop communication. However, in the process of clustering, selection of the CHs performs a very crucial role for saving the energy and therefore improving the network lifetime as it has several impacts on the energy conservation of member sensor nodes. Several number of clustering algorithms based on heuristic methods have been developed for WSNs [1-4]. LEACH algorithm is one of the well-known distributed clustering algorithm, in which a cluster head is selected with some probability among the sensor nodes to save more energy, however, the remaining energy is not considered for cluster head selection. Therefore, it is possible to select a sensor node with low energy as a cluster head which leads to die quickly [1]. In [5], Centralized LEACH is proposed which the distance and the energy of the nodes are also considered in cluster head selection. In [6], the cluster head selection is done using particle swarm algorithm (PSO) algorithm and the ratio of total initial energy of all nodes to the total current energy of the all cluster heads is considered, however, the distance from sink is not considered. In [7], residual energy, distance and node density is considered in cluster head selection. However, the cluster formation phase is ignored which it leads to have high energy consumption. In [8], a novel Energy Efficient Connected Coverage (EECC) scheduling is proposed to maximize the lifetime of the WSN. The EECC adheres to Quality of Service (QoS) metrics such as remaining energy, coverage and connectivity. In EECC the sensor which doesn't contribute to coverage will act as a relay node to reduce the burden of the sensing node. In [9], the paper introduces an algorithm named Fuzzy logic based unequal clustering, and Ant Colony Optimization (ACO) based Routing, Hybrid protocol for WSN to eliminate hot spot problem and extend the network lifetime. This protocol comprises of Cluster Head (CH) selection, inter-cluster routing and cluster maintenance. In [10], Extended-Multilayer Cluster Designing Algorithm (E-MCDA) approach is proposed in a large network. Performance of E-MCDA is evaluated in energy consumption at various aspects of energy, packets transmission, the number of designed clusters, the number of nodes per cluster and un-clustered nodes.

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Another important issue is the base station (BS) localization which is a critical factor in designing a wireless sensor network. Using this method, less power consumes to deliver the cluster head's data to BS. As a consequence, the network lifetime is improved. However, in some papers, BS location is deployed within the center point of the area of interest [11]. Although it gives fast suitable solutions, it cannot guarantee the optimal BS location. In [12], two algorithms are proposed to determine the optimal location of the base station; for homogeneous nodes as well as for heterogeneous nodes where the single-hop routing is used. The limitation of this approach is the high energy consumptions of the nodes located far from the sink. In [13], one approach is proposed based on PSO algorithm for determining the best position of the sink where multi-hop communication is considered. But in multi-hop communication the data collected by all the sensors reach the sink through the nodes close to the sink and thus these nodes may die soon due to pass a huge amount of data.

Therefore, our contribution in this paper is as follows:

- At first, we propose an energy efficient BS localization using PSO algorithm. Then, for saving more energy, the problem of the cluster heads selection is considered. In this case, sensors send their data to their corresponding cluster heads. The number of cluster heads which are selected among the sensors, are fixed. However, for cluster head selection, the remaining energy of each sensor and also its distance from BS is considered.
- After the cluster head selection, the proper position of BS is also determined using PSO algorithm to conserve more energy. Simulation results show the effectiveness of the proposed algorithm in improving the network lifetime.

The remainder of this paper is organized as follows. The network model is detailed in Section 2. The overview of PSO (Particle Swarm Optimization) technique is stated in section 3. The proposed algorithms based on PSO algorithm are shown in section 4. Performance evaluation results that demonstrate the efficiency of the proposed algorithms are presented in Section 5. Conclusions are drawn in Section 6.

2. Network Model

We consider a WSN deployed in a square area with a set of normal sensor nodes and high energy Base Station (BS). Normal sensor nodes sense local data about the environment and forward them to BS. Nodes can be deployed manually or randomly in the target area (Fig.1).

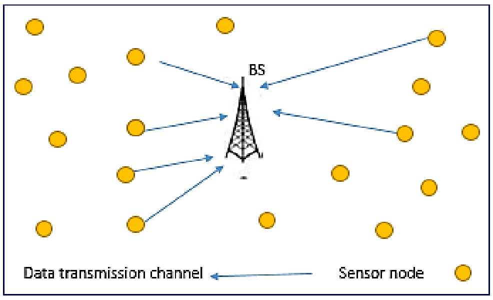

Fig. 1. Sensor node locations for data transmission.

As we said, sensor nodes in wireless sensor networks are energy constrained and cannot be rechargeable. Since battery is the only power source to the sensors, their energy should be carefully utilized to increase the network lifetime and improve its performance. The energy model used in this paper is based on two parameters [1]: E_{t-elec} is the transmitter electronics energy, E_{amp} is the required amplification. The energy consumption of each node depends on the amount of the data and also distance between each node and its receiver. In this paper, we assume that L reliable bits are transmitted to BS. Therefore, the total energy consumption is obtained as follows [14].

$$E_T = \sum_{j=1}^{N} L(E_{t-elec} + E_{amp} {d_j}^2) \quad (1)$$

Where N is the number of sensors and d_j is the distance between the jth node and BS. According to Eq.(1), the energy consumption is related to the distance between each node and BS. On other hand, BS should be located in a proper position from the sensors to save more energy. In fact, the suitable location of BS leads to increase the residual energy of the nodes. Therefore, the network lifetime is improved. We define the network lifetime to be the time until 25 percent of the sensors run out of energy [15], [16]. For this purpose, we use PSO algorithm as a random optimization algorithm to find the optimal position of BS. This algorithm was developed through the inspiration of social behavior of birds flocking. The details of this algorithm is at the next section.

3. Overview of PSO

PSO is a nature inspired swarm intelligence based algorithm, modelled after observing the choreography of a flock of birds, i.e., how they can explore and exploit the multi-dimensional search space for food and shelter [17], [18]. PSO consists of a predefined number of particles, M, called swarm. This algorithm searches the area with respect to the mathematical formula over velocity and position of each particle, $P_i, 1 \leq i \leq M$. A fitness function is used to evaluate each particle for verifying the quality of the solution. The objective of PSO is to find the particle's positions that result best evaluation of the given fitness function. PSO is initialized with a group of random particles (solutions) and then searches for optimal solution by updating iterations. In each iteration, each particle finds its own best, i.e., personal best called $Pbest_i$. Another "best" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the population. This best value is a global best and called $Gbest$. In each iteration, velocity of each particle is updated using the current velocity of the particle and the previous local best and global best position. Depending upon the past value, new velocity and new position of the particles can be estimated. The same procedure is repeated for each iteration. The formula for updating velocity and position of each particle is given by the following equations [19].

$$V_{p_i}(k+1) = w.V_{p_i}(k) + c_1.r_1(k)\left(Pbest_i - X_{p_i}(k)\right) + c_2.r_2(k)\left(Gbest - X_{p_i}(k)\right) \quad (2)$$

And

$$X_{p_i}(k+1) = V_{p_i}(k+1) + X_{p_i}(k) \quad (3)$$

Where, V_{p_i} and X_{p_i} are the new velocity and position of the ith particle, respectively. w is the inertia weight, c_1 and c_2 are the acceleration coefficients and $r_1(k)$ and $r_2(k)$ are random numbers uniformly distributed in [0,1]. The updating process is repeated until it is reached to an acceptable value of $Gbest$. After getting new updated position, the particle evaluates the fitness function and updates $Pbest_i$ as well as $Gbest$ for the minimization problem as follows [20].

$$Pbest_i = \begin{cases} E_{T_i} & \text{if fitness}(P_i) < Pbest_i \\ Pbest_i \text{ doesnot change} & \text{otherwise} \end{cases} \quad (4)$$

$$Gbest = \begin{cases} Pbest_i & \text{if } Pbest_i < Gbest \\ Gbest \text{ doesnot change} & \text{otherwise} \end{cases} \quad (5)$$

4. Proposed Algorithm

4.1 Proposed Algorithm without Clustering

As we said, in this paper, our aim is improving the network lifetime. For this purpose, we use PSO algorithm to find the optimal location of BS. According to PSO algorithm, each particle, P_i, shows the random coordinate of BS which lies in the corresponding environment. According to this position, the energy consumption of each sensor node for data transmission to each particle is calculated. The fitness function is the total energy consumption of all sensors in data transmission to BS. Our aim is to minimize the fitness function by determining the best location of BS. Therefore, the personal best (i.e., $Pbest_i$) is calculated for each particle through their fitness value. Then, the global best (i.e., $Gbest$) is calculated based on the $Pbest_i$ values according to Eq.(5). In learning algorithm, in each iteration the velocity and position of each particle are updated according to Eq.(2) and Eq.(3), respectively. Then, the fitness function is calculated again according to Eq.(1). According to this function, $Pbest_i$ and $Gbest$ are obtained. It should be noted that the sensor nodes are participated in data transmission which have enough energy. It means that their remaining energy is more than their energy consumption. The algorithm ends when the termination criteria is fulfilled. The pseudo code for the PSO-Based BS Localization Algorithm (PBBSL) is as below.

PBBSL Algorithm

While (Number of alive nodes>0.25*total number of nodes)
Determine the nodes which their remaining energy are more than their energy consumption
Initialize the particles P_i $\forall i \in M$(M is the number of particles)
For $i = 1$: M
Calculate the Fitness (E_{T_i})for each P_i
$Pbest_i = E_{T_i}$
End
$Gbest = \min(E_{T_i})$
While(termination criteria is not satisfied)
For $i = 1$: N
Update velocity and position of the particles P_i
Calculate Fitness(E_{T_i})
If Fitness of P_i< $Pbest_i$
$Pbest_i$=E_{T_i}
If Fitness of P_i< $Gbest$
$Gbest$= $Pbest_i$
End
End`
End
End
Compute the energy consumption for each node
Compute the remaining energy for each sensor
End while

Fig. 2. Pseudo code for PBBSL algorithm

4.2 Proposed Algorithm with Clustering

In our network model, it is possible that some sensing nodes are located in far distances from BS. Therefore, energy consumption for transmitting data to BS increases. In our system model one solution for saving energy is that, sensor nodes send their data to the cluster heads (CH). CH is a node among all sensors and it sends the data of the sensor nodes to BS.

In this section, the main purpose is selecting the cluster heads by considering the energy efficiency so that the network lifetime is improved. For cluster head selection, the residual energy of the sensor nodes and also the distance of each cluster head with other nodes which transmit data to the cluster head, are considered. Then, according to the cluster heads' position, the best location of BS is obtained according to PSO algorithm. For cluster head selection, the environment is divided at most into four squares and four nodes with enough energy and nearest to the middle of the squares are candidates as CHs. It should be noted that the environment is divided according to the number of the alive nodes. It means that for the empty square, there is not any cluster head. After the cluster head selection, finding the best location of BS is the similar to PBBSL algorithm, except that, the BS location is obtained according to the CHs' position. The flowchart of the proposed algorithm is shown in Fig. 3.

5. Performance Evaluation

In our wireless network, nodes are uniformly distributed in a square field with a length of 200 m. $E_{int} = 0.2$mJ is assumed as the initial energy for each sensor and the alive nodes are considered as the nodes that their remaining energies are more than the energy required for data transmission to CHs. CHs send the results of data transmitted from their corresponding nodes to BS. L = 10 bits are considered for data transmission. In all comparisons the exact optimal results are numerically obtained in MATLAB. Every simulation result in this section is averaged over 10000 realizations. We model the wireless channel between each sensor and CHs and also between each CH and BS using a free-space path loss model. By assuming a data rate of 250 kb/s and a transmit power of 20 mW, we consider E_{t-elec}=80 nJ [21],[22]. The E_{amp} to satisfy a receiver sensitivity of -90 dBm is $40.4 pJ/m^2$ [23].The parameters of PSO are in table1.

Table 1. Parameters for PSO in simulation

Parameter	Value
c_1	2
c_2	2
w	0.3
M	10

For showing the effectiveness of our proposed algorithms, we compare them with the following algorithms:

- Random BS Localization (RBSL) Algorithm: In this algorithm, BS position is selected randomly in each iteration. Then, the sensors send their data to BS. This algorithm has the minimum complexity to find the solution for our problem.
- Fixed BS Localization (FBSL) Algorithm: In this algorithm, BS location is fixed in environment and its position does not change according to the alive nodes location. This algorithm is considered to show that determining the location of BS improves the network lifetime.

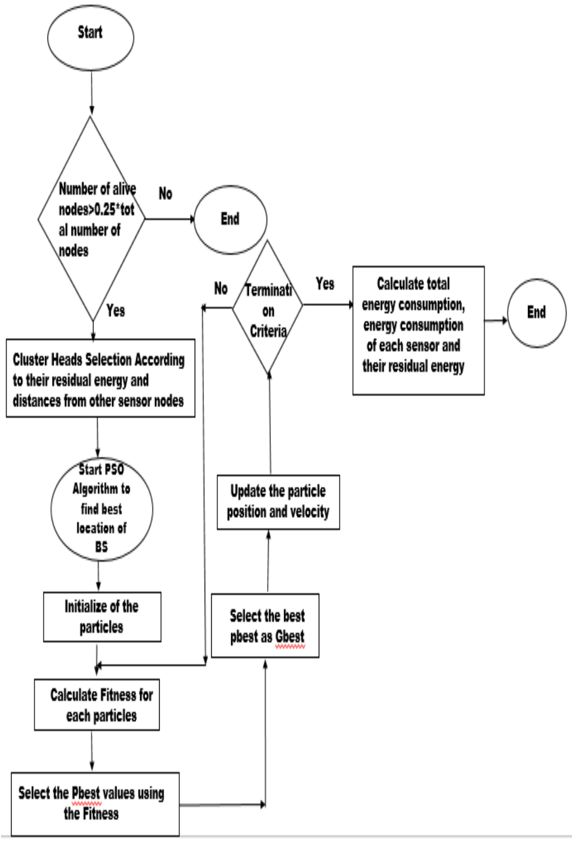

Fig. 3. Flowchart of the proposed algorithm with CHs selection

Fig. 4 shows the number of alive nodes for different algorithms. It is clear that in PBBSL algorithm with clustering, number of alive nodes is more than the other algorithms. PBBSL algorithm also have more alive sensors than RBSL and FBSL algorithms due to the random and fixed position of BS. In this case, it is possible to locate more sensors far from BS and therefore, the energy consumption is increased significantly. In fact, more alive sensors states more lifetime for the network. On the other hand, cluster heads and BS localization lead to improve the network lifetime. The dimension of the environment is set to 1000m.

Fig. 5 shows the average total remaining energy of the nodes. It is clear that cluster head selection leads to save more energy in sensors due to the decreasing the distance for data transmission. We also note that determining the location of BS according to the CHs position helps to have more remaining energy for CHs. It should be noted that in less number of nodes, cluster head selection is not effective in saving energy, however, increasing the number of sensors show the effectiveness of the cluster head selection in having more remaining energy. According to the results, RBSL and FBSL algorithms have lower remaining energy. On the other hand, they have lower alive sensors due to the random position and fixed position for BS, respectively.

Fig. 6 shows the average total energy consumption versus different nodes. According to the results, CHs selection and determining the location of BS increases the energy consumption of the nodes for data transmission to CHs and also data transmission from CHs to BS. It shows that there are more alive sensors to transmit their data to the cluster heads or BS while in FBSL and RBSL, the energy consumption is decreased because less nodes are still alive to send their data to their destination. It should be noted that as the number of the sensors increases, more energy consumes due to the existence of more alive nodes in the environment.

In Fig. 7 the total remaining energy of the sensors for different algorithms is shown. In fact, this metric states the successful percent of the algorithms in balancing the energy consumption of the alive sensors. Our proposed algorithms have the highest value of the total remaining energy. Therefore, the network lifetime is improved. According to the results, by increasing the dimension of the environment, the total remaining energy is increased. Because, it is possible to have more sensors far from BS and hence, the energy consumption increases. The number of sensors is set to 50.

Fig. 8 shows the number of alive nodes for different algorithms. In fact, this metric states the role of the algorithms for increasing the network lifetime. According to the results, our proposed algorithms have the most network lifetime while FBSL and RBSL algorithms have the least value. It means that clustering and BS localization improve the network lifetime significantly. It should be noted that only the sensors with enough energy participate in data transmission.

Fig. 9 shows the total energy consumption of different algorithms versus different environments. Although, our proposed algorithms consume more energy for data transmission, however, there is a balance between the sensors for sending data. On the other hand, more alive nodes consume more energy to transmit their data to BS or cluster heads. FBSL and RBSL algorithms consume less energy due to the less number of alive nodes. It should be noted that as the dimension of the environments increases the energy consumption increases due to the more distances between sensors and cluster heads.

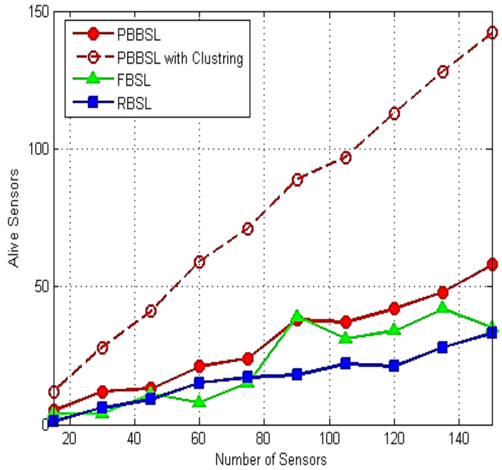

Fig. 4. Number of alive sensors versus different sensors

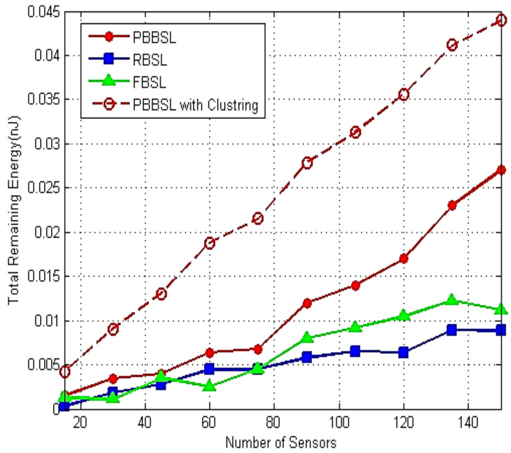

Fig. 5. Total remaining energy versus different sensors

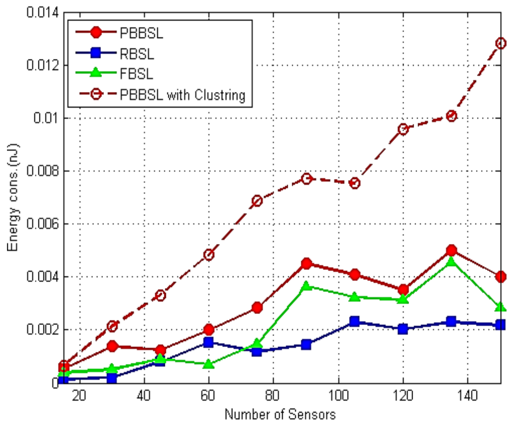

Fig. 6. Total energy consumption versus different sensors

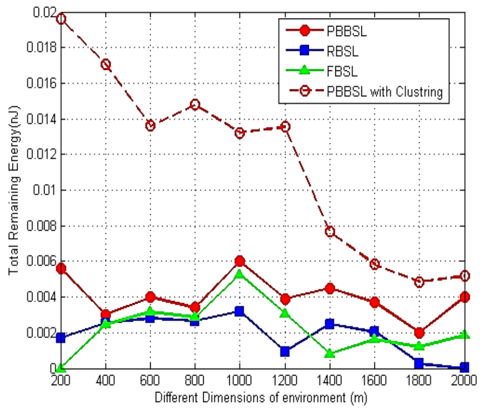

Fig. 7. Total remaining energy versus different environments

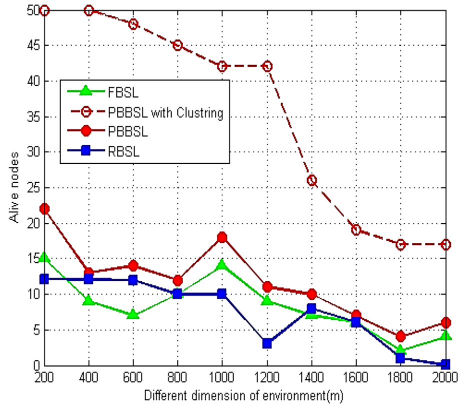

Fig. 8. Number of alive sensors versus different environments

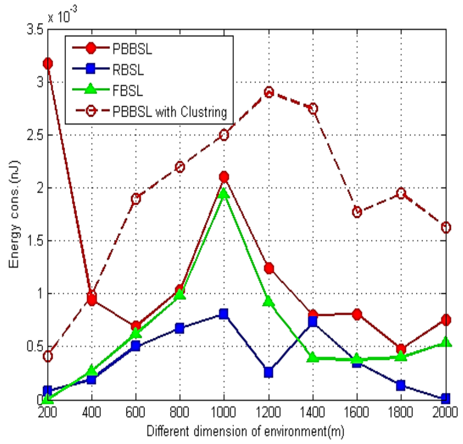

Fig. 9. Total energy consumption versus different environments

6. Conclusions

Wireless sensor networks have multiple applications in intelligent environment and structural monitoring. However, in wireless sensor networks, one of the most critical challenges is the power constraint of the sensors. In this paper, we proposed an algorithm based on PSO algorithm to improve the lifetime of the network. For this purpose, at first, the cluster heads are selected among the sensors according to their remaining energy and distances from other nodes. Then, the suitable position of BS is obtained based on the cluster heads position using PSO algorithm. By the proposed algorithm, the energy consumption of the nodes are more saved and the residual energy is increased. It means that the sensors have more opportunity to be alive and monitor the environment. The simulation results showed the effectiveness of the proposed algorithm in lifetime improvement in different situations. Cluster head selection using the other algorithms and using the mobile sensor networks can be applied as the future work of this paper.

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