A Discrete Particle Swarm Optimization Based Clustering Algorithm for Wireless Sensor Networks

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Abstract. Clustering is a widely used mechanism in wireless sensor networks to reduce the energy consumption by sensor nodes in data transmission. Partitioning the network into optimal number of clusters and selecting an optimal set of nodes as cluster heads is an NP-Hard problem. The NP-Hard nature of clustering problem makes it a suitable candidate for the application of evolutionary algorithm and particle swarm optimization (PSO). In this paper, we shall suggest a PSO based solution to the optimal clustering problem by using residual energy and transmission distance of sensor nodes. Simulation results show a considerable improvement in network lifetime as compared to existing PSO based algorithms and other clustering protocols like LEACH and SEP.

1 Introduction

The use of wireless sensor network has grown enormously in last decade. Wireless sensor networks are used in variety of applications such as monitoring physical and environmental conditions, military surveillance, live stock tracking, home appliance monitoring etc. In most wireless sensor network (WSN) applications nowadays the entire network must have the ability to operate unattended in harsh environments in which pure human access and monitoring cannot be easily scheduled or efficiently managed or it's even not feasible at all [1]. There is a crucial need for scalable and energy efficient routing and data gathering and aggregation protocols in corresponding large-scale environments. In many significant WSN applications the sensor nodes are often deployed randomly in the area of interest by relatively uncontrolled means and they form a network in an ad hoc manner [2, 3]. Sensors in such networks are battery powered and energy constrained and their batteries usually cannot be recharged. Therefore we need energy aware routing and data gathering protocols that offer high scalability and low energy consumption for a long network lifetime. In wireless sensor network hundreds to thousands of sensor nodes are deployed usually randomly. Sensors sense their environment and send their sensed data to a processing centre, called as "Sink" or "Base Station" where all the data is collected and processed [4]. Many routing algorithms have been proposed for efficient transmission of data between base station and sensor nodes. Grouping of sensor nodes into clusters has been widely used by researchers to satisfy the scalability,

© Springer International Publishing Switzerland 2015
S.C. Satapathy et al. (eds.), *Emerging ICT for Bridging the Future – Volume 2,*
Advances in Intelligent Systems and Computing 338, DOI: 10.1007/978-3-319-13731-5_16

high energy efficiency and prolong network lifetime objectives. In clustering the whole sensor network is partitioned into multiple groups of sensor nodes. Each group is called a cluster and each cluster has a leader called cluster head that perform special tasks such as data aggregation and fusion. In addition to supporting network scalability and decreasing energy consumption through data aggregation, clustering has numerous other secondary advantages and corresponding objectives. It can localize the route setup within the cluster and thus reduce the size of the routing table stored at the individual node. It can also conserve communication bandwidth by limiting the scope of inter-cluster communication among CHs and reduce redundant exchange of messages among sensor nodes. Moreover, clustering can stabilize the network topology at the level of sensors and thus cuts on topology maintenance overhead [1] [2] [5].

2 Related Work

Various clustering based routing algorithm has been proposed for efficient utilization of energy of sensor nodes in wireless sensor networks.

LEACH [3] is one of the most popular and widely used probabilistic clustering algorithm that use randomized rotation of CHs and a distributed process of cluster formation based on some priori optimal probability. Many modifications such as LEACH-C [4], LEACH-M [5] etc, to the original LEACH protocol have been proposed.

HEED [6] is another improved and very popular energy efficient protocol. It is a hierarchical, distributed, clustering scheme in which a single-hop communication pattern is retained within each cluster, where as multi-hop communication is allowed among CHs and the base station.. The CH nodes are chosen based on two basic parameters, residual energy and intra-cluster communication cost.

PSO-C [8] is a centralized, PSO based Clustering Algorithm that aims to minimize intra-cluster communication.

EEHC is a probabilistic clustering protocol proposed in [7].The main objective of this algorithm was to address the shortcomings of one-hop random selection algorithms such as LEACH by extending the cluster architecture to multiple hops. It is a distributed, *k*-hop hierarchical clustering algorithm aiming at the maximization of the network lifetime.

In [9] the authors propose such a swarm intelligence-based clustering algorithm based on the ANTCLUST method. ANTCLUST is a model of an ant colonial closure to solve clustering problems. In colonial closure model, when two objects meet together they recognize whether they belong to the same group by exchanging and comparing information about them. In the case of a WSN, initially the sensor nodes with more residual energy become CHs independently. Then, randomly chosen nodes meet each other, exchange information, and clusters are created, merged, and discarded through these local meetings and comparison of their information.

3 Particle Swarm Optimization

Particle swarm optimization (PSO), developed by Dr. Eberhart and Dr. Kennedy in 1995 and inspired by social behaviour of bird flocking or fish schooling is a population based stochastic technique to solve continuous and discreet optimization problems,.

PSO learned from the scenario and used it to solve the optimization problems. In PSO, each single solution is a "bird" in the search space. We call it "particle". All of particles have fitness values which are evaluated by the fitness function to be optimized, and have velocities which direct the flying of the particles. The particles fly through the problem space by following the current optimum particles [10].

PSO is initialized with a group of random particles (solutions) and then searches for optima by updating generations. In each iteration, each particle is updated by following two "best" values. The first one is the best solution (fitness) it has achieved so far. (The fitness value is also stored.) This value is called pbest. 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. When a particle takes part of the population as its topological neighbours, the best value is a local best and is called lbest [11].

Suppose, there is a group of K random particles in an n-dimension searching space, the position of the ith particle is $X_i = (x_{i_1}, x_{i_2}, \dots \dots., x_{i_n})$, the personal best value of the particle is $pbest_i = (p_{i_1}, p_{i_2}, \dots \dots., p_{i_n})$, and the velocity of the particle is $V_i = (v_{i_1}, v_{i_2}, \dots \dots., v_{i_n})$. The best value obtained so far by any particle in the population is $gbest = (g_1, g_2, \dots \dots., g_n)$. After finding the two best values, pbest and gbest the particle updates its velocity and positions as follows

$$v_{i_j} = w.v_{i_j} + c_1.r_1\left(p_{i_j} - x_{i_j}\right) + c_2.r_2\left(g_j - x_{i_j}\right) \tag{1}$$

$$x_{i_j} = x_{i_j} + v_{i_j} \tag{2}$$

Where w is inertia and used to control the trade-off between the global and the local exploration ability of the swarm, c1 and c2 are learning factors, r1 and r2 random numbers between 0 and 1.

4 Proposed Algorithm

In this section we describe in detail the working of our proposed algorithm. We assume a wireless sensor network with sensor nodes uniformly distribute across the network. We also assume that location of Base station is fixed inside or outside the sensor network and location of sensor nodes is also known to base station.

4.1 Radio Energy Model

For energy dissipation inside a sensor node for transmitting the data, the first order radio energy model as described in [3] is used.
In order to achieve an acceptable SNR to transmit an L bit message to a node situated at distance d, the energy consumed by radio is given by-

$$E_{Tx}(L,d) = \begin{cases} L.E_{elec} + L.\varepsilon_{fs}.d^2 & \text{if } d \le d_0 \\ L.E_{elec} + L.\varepsilon_{mp}.d^4 & \text{if } d > d_0 \end{cases} \tag{3}$$

Where E_{elec} is the energy, dissipated per bit to run the transmitter or the receiver circuit, ε_{fs} and ε_{mp} depend on the transmitter amplifier model, and d is the distance between the sender and the receiver; By equating the two expressions at $d = d_0$, we get, $d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}}$.

To receive an L–bit message the radio expends-

$$E_{Rx} = L.E_{elec} \tag{4}$$

4.2 Fitness Function

Success of our proposed algorithm will depend greatly on the formulation of fitness function. So we are defining a fitness function that includes all optimization criteria. Our aim is to minimize the intra-cluster communication energy and energy loss due to cluster head and base station communication, so we can define the fitness of a particle i as

$$F(P_i) = E_1(P_i) + \mu\, E_2(P_i) \tag{3}$$

$$E_1(P_i) = \sum_{k=1}^{K} \sum_{\forall n_{k_j} \in C_k} \frac{f(n_{k_j}, CH_k) - E_{min}}{E_{max} - E_{min}} \tag{4}$$

$$E_2(P_i) = \sum_{k=1}^{K} \frac{g(CH_k, BS) - E_{min}}{E_{max} - E_{min}} \tag{5}$$

$$f\left(n_{k_j}, CH_k\right) = \begin{cases} s^2\left(n_{k_j}, CH_k\right) & if\ s\left(n_{k_j}, CH_k\right) \le d_0 \\ s^4\left(n_{k_j}, CH_k\right) & if\ s\left(n_{k_j}, CH_k\right) > d_0 \end{cases} \tag{6}$$

$$g(CH_k, BS) = \begin{cases} d^2_{CH_k,BS} & if\ d_{CH_k,BS} \leq d_0 \\ d^4_{CH_k,BS} & if\ d_{CH_k,BS} > d_0 \end{cases} \tag{7}$$

$$s(n_i, CH_k) = \begin{matrix} min\ (s_{n_i,CH_k}) \\ \forall k = 1,2,\dots,K \end{matrix} \tag{8}$$

Where, $d_{i,j}$ is the distance between node i and node j; s is a function that find the minimum distance cluster head for a given node; f is a function whose value for a given node is proportional to the energy consumed in communication between the node and its cluster head; similarly g signifies the energy loss due to cluster head and base station communication; E_{max} and E_{min} are the maximum and minimum energy loss in the network. C_k is kth cluster in a solution or particle.

E_1 and E_2 are two normalized functions that represent the energy dissipated in intra-cluster communication and due to communication between sink and CHs respectively. F is fitness function and our aim is to minimize this function.

μ is a controlling parameter that control the distance between base station and cluster heads. The higher the value of μ will be the closer will be the CHs from BS. K is the optimal number of cluster heads.

For each particle or solution we will choose k random nodes as cluster heads and remaining nodes will join the cluster whose CH is at minimum distance from it.Then we will evaluate the value of fitness function for each particle and will calculate pbest and gbest. Then we will update the velocity vector and position vector according to equation (1) and (2).

4.3 A New Operator $\oplus_{NW}$

We will define a new operator $\oplus_{NW}$ that when applied on a location with respect to a network, will return a valid sensor node location in the network. In each iteration of our algorithm we will update the location of CHs in each particle or solution. Keeping this into consideration we define $\oplus_{NW}$ as follows:

Suppose $\dot{a} = (a_1, a_2)$ is any location with respect to a sensor network NW then $\oplus_{NW}\ \dot{a}$ will return a valid location in network NW. The operator $\oplus_{NW}$ will first check if $\dot{a}$ a valid location in network or not. If $\dot{a}$ is a valid location than it return $\dot{a}$ as it is; if not then it will return nearest valid location in the network NW toward base station with highest residual energy. After calculating new velocity and position using equation (1) and (2) we will apply our operator to the calculated positions to get valid new positions.

4.4 Clustering Algorithm

```
1.  Create and initialize a K-dimensional swarm of P
    particles by choosing K CHs with residual energy
    higher than average energy of network for each
    particle.
2.  repeat
3.  for each particle i = 1,2,...,P do
4.        if F(X_i) < lbest_i then
5.              lbest_i = X_i
6.        end
7.        if F(X_i) < gbest then
8.              gbest = X_i
9.        end
10. end
11. for each particle i = 1,2,...,P do
12.       update velocity V_i using equation (1)
13.       update  position vector X_i using equation(2)
14.       apply ⊕_NW operator to updated position
15. end
16. until the maximum number of iteration reached
```

5 Simulation Results

For simulation we assume a square network field of size 100m X 100m with 100 sensor nodes deployed uniformly in it. We assume that sink is at the centre of the field. We will compare the performance of our proposed algorithm with LEACH and its popular variant LEACH-C. We are using same simulation parameters are described in Table 1. Figure 1, 2 and 3 show the no. of alive nodes in each round of LEACH, LEACH-C and our proposed protocol PSOBC. Simulation results show a considerable improvement in network lifetime.

Table 1. Simulation Parameter

Description	Parameter	Value
Initial energy	E_0	0.5J
Electronic circuitry energy	E_{elec}	50nJ/bit
Multi-path co-efficient	ε_{mp}	10 pJ/bit/m2
Free space co-efficient	ε_{fs}	0.0013 pJ/bit/m4
Data aggregation energy	E_{DA}	5 nJ/bit/signal
Total no. of nodes	N	100
Optimal percentage of CHs	P_{opt}	0.1

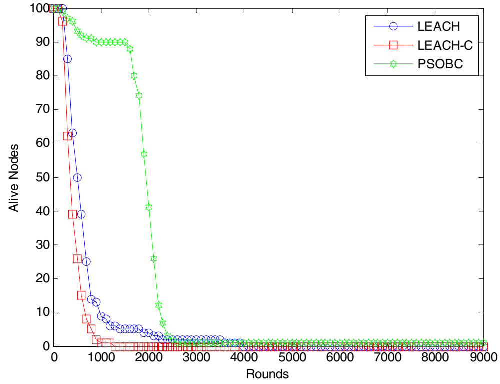

Fig. 1. Alive nodes per round for BS position (50, 0)

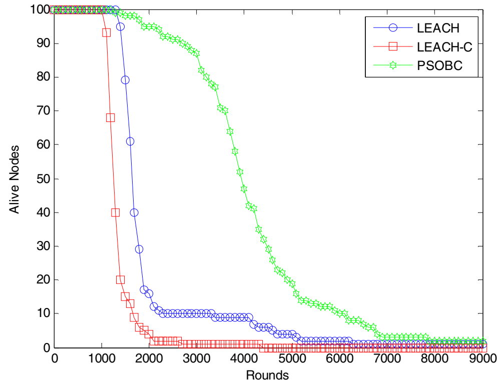

Fig. 2. Alive nodes per round for BS position (0, 50)

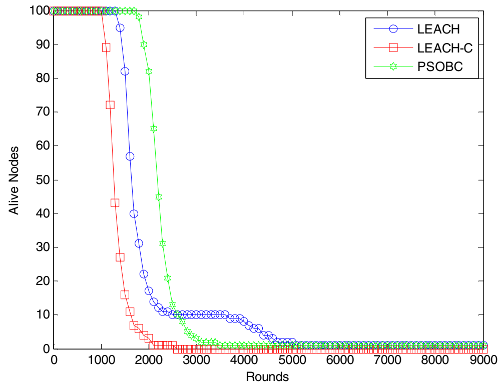

Fig. 3. Alive nodes per round for BS position (200, 200)

6 Conclusion

In this work we proposed a PSO based solution to clustering problem. We used same PSO algorithm that is used for continuous search space with little modification. We defined a new operator and used it with original PSO algorithm to make it work with discrete search space. Simulation results show a considerable increment in Network lifetime as compared to LEACH and LEACH-C. The main drawback of this easy and efficient solution is that it requires the presence of a central authority for cluster setup but it is not always possible in practical applications. We can use base station as central authority if it is not power constrained. The basic idea here was to optimize intra cluster communication energy and energy loss due to communication between CHs and base station by using PSO and by using base station as centralized authority for cluster set up in the network.

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