Biologically Inspired Low Energy Clustering for Large Scale Wireless Sensor Networks

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Abstract. The recent technological advances in data gathering, embedded micro-devices and mobile networking has significantly advanced the applications of small-size and numerous tiny nodes. Large scale wireless sensor networks (LSWSNs) are intensively studied and used in the fields of traffic avoidance, intelligent family, medical diagnostic, environmental, multimedia surveillance, military affairs and so on. The recent success of emerging LSWSNs technology has encouraged researchers to develop new low energy clustering algorithm in this field. In LSWSNs, reducing communication energy consumption of sensor will not lead to maximize network lifetime for the total system. The low energy clustering is a typical NP-hard combinatorial optimization problem. In this paper, an immune adaptive cuckoo search algorithm (IACSA) is given to reduce total energy consumption. We first design a fitness function to evaluate energy consumption of system. The IACSA is designed to improve the energy efficiency for LSWSNs. It has the advantages of immune generator that takes into account different benefits and adaptive operator to enhance the convergence rate. Simulations are conducted to show a comparison of IACSA with the shuffled frog leaping algorithm (SFLA), particle swarm optimization (PSO) and artificial fish swarm algorithm (AFSA). Results show that the proposed IACSA has lower energy consumption compared to the SFLA, AFSA and PSO, which means that the proposed method reduces the energy consumption.

1. Introduction

The rapid development of data gathering, embedded computing and networking technologies brings a lot of advantages on wireless communication [1]-[3]. Large scale wireless sensor networks (LSWSNs) consist of a great deal of sensors, which possess limited computation, sensing and free-infrastructure capabilities. Each sensor node is made up of five components, including the information collecting component, the microprocessor component, the transceiver component, the data storage component and the energy supply component [4]-[6]. LSWSNs are growing techniques in many aspects, such as tracking, military purposes, homeland security, environment surveillance, multimedia surveillance, medical diagnostic, etc [7][8].

Low energy clustering is a strategy offering an approach that displays how to reduce communication energy consumption in LSWSNs [9]. LSWSNs have been concerned in many fields for their large size with limited communicating capabilities. Low energy clustering scheme can be an effective optimization means for achieving the desired power consumption goals, comprising communicating capability constraints. The low energy clustering problem is an NP-hard problem and still one of the most exciting
challenges in the LSWSNs [10]. Nevertheless, as exhaustive search are required in every combination, the computational complexity is huge in the problem.

Heuristics which combined with swarm algorithm have shown great promise in low energy clustering. A shuffled frog leaping algorithm (SFLA) method for low energy clustering was first introduced in [11]. The proposed method is to improve the energy efficiency by using a hybrid heuristic technique. However, the rate of convergence could not reach an acceptable point. The application of artificial fish swarm algorithm (AFSA) in low energy clustering problem has been researched [12]. As of previous work of the authors, this method can reduce total energy consumption for better energy consumption optimization. The AFSA is a basic swarm strategy but this algorithm commonly yields a shorter network lifetime than evolutionary algorithms. In [13], particle swarm optimization (PSO) can improve the energy efficiency that has been investigated. The algorithm has good performance. Nevertheless, the rate of convergence could not reach an acceptable point.

In this paper, we present an immune adaptive cuckoo search algorithm (IACSA), a cuckoo search algorithm that exploits the low energy clustering scheme, and we show how to take advantage of immune theory to efficiently speed up the convergence speed. We first give a novel formulation of the objective function to maximize the energy consumption to satisfy the energy consumption optimization. We make use of the fresh immune and adaptive operators where they are employed to cuckoo search algorithm. In IACSA, an effective cuckoo search algorithm that blends the advantages of immune theory and adaptive theory is presented. So, the proposed method can raise global search capability and enhance the randomness in the process of investigation. Furthermore, with the adaptive operator strategy, IACSA can obtain higher precision solution and prevent premature convergence.

In the simulations, we compare the proposed IACSA with the SFLA, PSO and AFSA. Simulation results indicate that the IACSA provides a good choice to enhance the energy efficiency over other SFLA, AFSA and PSO schemes for LSWSNs.

2. System Model
The system model to solve the problem of low energy clustering with respect to the constraints is given in this section.

Since the LSWSNs are usually powered by a battery, and the replacement of the battery requires a relatively high cost. The energy consumption problem is an important issue in LSWSNs. If the communication energy consumption can be effectively reduced, the lifetime of LSWSNs can be prolonged, and the labour cost of replacing the battery can be reduced.

Communication energy consumption usually consists of transmitting energy consumption and receiving energy consumption. The energy consumption and reception can be calculated by (1) and (2):

\[ E_{CX}(l,d) = E_{elec} \cdot l + \varepsilon_{amp} \cdot l \cdot d^n \]
\[ E_{RX}(l) = E_{elec} \cdot l \]

In (1) and (2), \( E_{CX}(l,d) \) indicates the energy consumed to transmit \( l \) bit to a node of distance \( d \), and \( \varepsilon_{amp} \) is a parameter of power amplification. \( E_{elec} \) is a parameter of electronics energy. \( d \) is the distance between nodes. The value of \( n \) is determined by the specific problem. We take \( n=3 \) in this paper.

\[ E_j = E_{CX} + E_{RX} \]
\[ E_{SUM} = \sum_{j=1}^{j} E_j \]

In (3), \( E_j \) indicates the sum of energy consumption and reception of a node. In (4), \( E_{SUM} \) is sum of the total energy consumption of all nodes.
3. An immune adaptive cuckoo search algorithm for low energy clustering in LSWSNs

The cuckoo search algorithm can solve the continuous optimization problem, but it does not solve the binary or discrete problem. For the low energy clustering problem, a discretized optimization algorithm needs to be designed. The binary IACSA is used to optimize the energy efficiency. The discrete IACSA has three advantages, simple operation, fewer parameters, and don’t need to re-match parameters when deal with optimization problems.

In essence, the IACSA has three elements: optimal selection, local random flight, and global Lévy flight.

To simplify the description of the IACSA, assume the following three idealization rules.
(1) Each cuckoo has only one egg at a time, that is, there is an optimal solution, and the nest is randomly selected when it hatches;
(2) The optimal nest and optimal solution are retained to the next generation;
(3) The number of nested main birds is fixed, and the probability that cuckoo hatching eggs are found by nesting birds is also fixed as $P_a \in [0, 1]$. When the cuckoos in house either throw the egg out of the nest or discard the nest to find another place and build a new nest.

3.1. Population Encoding and Initialization

Population encoding is the first step, which applies in the IACSA to solve the low energy clustering problem. According to the low energy clustering problem applied by IACSA, the corresponding encoding method, such as binary encoding, is adopted. The position of the nest is composed of binary code, that is, the variable takes 0 or 1.

During the formation of the cluster, each sensor node is assigned a random number between 0 and 1. When the value is 1, the node is adopted as cluster head node. Otherwise, the node is employed as sensor node.

Supposed the population $P$ is composed of $I$ individuals, $P = \{P_1, P_2, \ldots, P_I\}$. The encoding population can be shown in (5).

$$
P = \begin{bmatrix}
P_{1,1} & p_{1,2} & \cdots & p_{1,J-1} & p_{1,J} \\
p_{2,1} & p_{2,2} & \cdots & p_{2,J-1} & p_{2,J} \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
p_{I-1,1} & p_{I-1,2} & \cdots & p_{I-1,J-1} & p_{I-1,J} \\
p_{I,1} & p_{I,2} & \cdots & p_{I,J-1} & p_{I,J}
\end{bmatrix}
$$

In (5), $I$ represents the amount of cuckoos, $i \in \{1, 2, \ldots, I\}$, $J$ indicates the quality of sensor nodes, $j \in \{1, 2, \ldots, J\}$, $p_{i,j} = 1$ indicates that the $j_{th}$ node in the $i_{th}$ cuckoo is the cluster head node. When $p_{i,j} = 0$, the $j_{th}$ sensor node in the $i_{th}$ individual cannot be applied as cluster head node.

$$
\sum_{j=1}^{J} p_{i,j} = K
$$

In (6), $K$ is employed as the amount of cluster heads. The number of cluster heads must equal to $K$.

In population $P$, each individual has energy consumption and reception. $E = \{E_1, E_2, \ldots, E_I\}$, $E$ indicates the sum of energy consumption and reception.

3.2. Fitness Calculation

In order to optimize the communication energy consumption, we establish a fitness function based on two factors of energy consumption and reception in (7). The cuckoos will be selected to the next iteration when the energy consumption is lower.
\[ f = \sum_{j=1}^{J} E_j \quad (7) \]

3.3. Lévy Flight
In discrete IACSA algorithm, a nest represents a solution, and the position of one nest is randomly initialized in the feasible solution space defined by the objective function. The most important step of the IACSA is the location update. The equations of Lévi flight of the first method are as follows:

\[ \text{Sig}(\text{step}) = \frac{1}{1 + \exp(-\text{step})} \quad (8) \]

\[ p_{ij}^{t+1} = \begin{cases} 1 & \text{if rand } \leq \text{Sig}(\text{step}) \\ 0 & \text{otherwise} \end{cases} \quad (9) \]

Where \( \text{step} \) is the step of the Lévy flight, \( \text{Sig}() \) indicates sigmoid function. \( p_{ij}^{t+1} \) is the binary code of the \( j \)th dimension and the position of the \( i \)th bird's nest in the \( (t+1) \)th generation, and \( \text{rand} \) is a completely random number in [0, 1].

The second method is as follows:

If \( \text{step} \leq 0 \),

\[ \text{Sig}(\text{step}) = 1 - \frac{2}{1 + \exp(-\text{step})} \quad (10) \]

\[ p_{ij}^{t+1} = \begin{cases} 0 & \text{if rand } \leq \text{Sig}(\text{step}) \\ \text{p}_{ij}^{t} & \text{otherwise} \end{cases} \quad (11) \]

If \( \text{step} > 0 \),

\[ \text{Sig}(\text{step}) = \frac{2}{1 + \exp(-\text{step})} - 1 \quad (12) \]

\[ p_{ij}^{t+1} = \begin{cases} 1 & \text{if rand } \leq \text{Sig}(\text{step}) \\ \text{p}_{ij}^{t} & \text{otherwise} \end{cases} \quad (13) \]

3.4. Immune Operator
In the low energy clustering of LSWSNs, the coding sequence is long, which leads to the slow optimization process of IACSA, which easily leads to the stagnation of iterative process. The IACSA is a heuristic optimization algorithm that combines the information processing mechanism of biological immune system.

The steps of IACSA with immune operator include: encoding of antibodies, generation of initial antibodies \( P \), calculation of antibody affinity \( f(P) \), antibody selection and clonal amplification, antibody replacement and retention.

Step 1: Randomly generate the initial antibody, that is, randomly generate a candidate solution, and create a total population \( P \), which consists of \( I \) initial antibodies.

Step 2: Calculate antibody affinity, affinity is the objective function \( f(P) \).

Step 3: Select the antibody with the lowest energy consumption from the population to form a temporary antibody set.

Step 4: Cloning antibodies with low affinity: the lower the energy consumption, the larger the size of the cloned antibody.
3.5. Adaptive Operator
Taking the parameter as a fixed value is not conducive to the global search and local search. In order to make the IACSA more efficient, the IACSA with an adaptive strategy makes $P_a$ change dynamically.

In the early stage of the IACSA, a relatively small $P_a$ is employed in the proposed method. The quantity of updated solutions is huge, so that the algorithm maintains strong global search ability, while taking into account the local search ability. In the later stage of the algorithm, a relatively large $P_a$ is employed, so that it can be improved the convergence speed of IACSA.

3.6. Termination Condition
The most common way of termination conditions is to give a maximum iteration times in advance, or to determine whether the optimization value is continuous. In this paper, we apply the first method.

3.7. Algorithm Steps
The specific steps of the IACSA algorithm are as follows:

Step1: Randomly generate $I$ individuals and calculate fitness. Filtering out the optimal individual, and retain to the next generation;

Step2: Lévi flight is conducted to create a new host nest location by using formula (7) to create a new population and calculate fitness.

Step3: Produce a random number $rand \in [0,1]$ obeying a uniform distribution, compared with the probability that the cuckoo is found by the bird's egg $P_a=0.25$, if $rand > P_a$ the bird's fitness is randomly changed, and vice versa, and then the updated bird's energy consumption, compared with the results that obtained in the previous step, the bird's nest position with lower energy consumption is taken, and the global minimum energy consumption is selected.

Step4: If the maximum number of iterations is reached, output the final solution, if not returning to step2.

4. Simulation and Results
In this section, we evaluate the efficiency of the IACSA by comparing with the AFSA, SFLA as well as PSO when deal with the problem of low energy clustering in LSWSNs. To examine the applicability for practical implementations, we evaluate the performance of the schemes on a PC with Pentium 2.40 GHz,2G RAM,WIN-7 OS, and MATLAB software.

After that, a fitness function to calculate the energy consumption is employed in this section. The coordinates of sensor nodes are then randomly chosen in the range of 0 to 400 m.

In the following experiments, the simulation parameters for the IACSA, SFLA, AFSA and PSO are given in following discussion. The results are obtained after the algorithm runs 100 times.

In IACSA, the number of nests is 50, and the probability of finding is 0.25. In PSO, the maximum velocity is definitely employed as 4. The cognitive and social values are $c_1=c_2=0.5$. The dynamic range of the particle is set to 0.4. The parameter values in the SFLA are given in following. The number of individuals in the population is 50, the number of subgroups is 10, and the number of individuals in the subgroup is 5. In AFSA, visual is 5. Step is 5. Try number is 10 and congestion factor is 0.6.

Figure 1 and figure 2 show the communication energy consumption of IACSA, SFLA, AFSA and PSO when the low energy clustering problem is solved with different quantity of sensor nodes. We set sensor nodes to 200 and 300, respectively, and cluster head proportion percentage is 10%. For each method, we select solution that yields the best results. The results are the average over 100 runs with different methods. To demonstrate the advantages of the IACSA, the optimization results from SFLA, AFSA and PSO approaches after 100 iterations are compared, as illustrated in the following figures.
The IACSA gives the minimum energy consumption, followed by the SFLA, AFSA and PSO. The quantity of energy consumptions is close to 158 by use of IACSA in the beginning of iterations in figure 1, which is lower than that of SFLA, AFSA and PSO. It is clear that the IACSA achieves better convergence rate than the SFLA, AFSA and PSO. Meanwhile, SFLA, AFSA and PSO maintained a nearly constant result due to its premature convergence. In the end of iterations, IACSA has the best results, which is 116. In comparison with the IACSA, the proposed SFLA, AFSA and PSO provide suboptimal results, and the values are equal to 129, 134 and 150 respectively. Figure 2 has the similar performance and effect as Figure 1.

Figure 3 and figure 4 demonstrate the energy consumption with different numbers of sensor nodes and the cluster head proportion is 10% and 20%, respectively. We also set sensor nodes to 200, 400, 600, 800 and 1000, respectively. Comparisons are also performed with SFLA, AFSA and PSO. After simulations, the proposed algorithm can reduce total energy consumption for better energy consumption optimization. So the proposed method has a better performance compared with SFLA, AFSA and PSO.

5. Conclusion
In this paper, an immune adaptive cuckoo search algorithm (IACSA) to reduce total energy consumption for the problem of low energy clustering is developed. In this work, we first propose a novel formulation of the objective function to improve the energy efficiency to satisfy the energy consumption optimization. The simulations are executed to display the effectiveness of the IACSA when compare
with SFLA, PSO and AFSA, where indicates that the low energy consumption clustering of the proposed IACSA method is better than that of SFLA, AFSA and PSO, respectively. IACSA has the ability to compute the approximate results with adaptive operator strategy to avoid local optima that may occur in searching process.

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