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A Routing Optimization Strategy for Wireless Sensor Networks Based on Improved Genetic Algorithm

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Abstract

In order to resolve the problem of generating invalid new individual when using genetic algorithm for routing optimization in wireless sensor networks (WSNs), an improved genetic algorithm (ROS_IGA) is put forward. By considering the position and neighbors of nodes in WSNs, ROS_IGA takes reasonable crossover and mutation operation to ensure compliance with the topological of actual WSNs and the demand of communication among nodes. Furthermore, ROS_IGA takes many factors, such as the residual energy of sensor nodes, distance and energy consumption between adjacent nodes, communication delay and relay hops, into consideration to select suitable routing. So ROS_IGA increases the speed of convergence and optimizes the performance of WSNs. Finally, a simulation experiment is carried out and the experimental results show that the improved algorithm in this study can effectively finds the best routing and decreases energy consuming and also increases the network life cycle.

Key Words: Wireless Sensor Network, Genetic Algorithm, Crossover, Mutation

1. Introduction

Wireless sensor networks (WSNs) are distributed autonomous sensors to monitor physical or environmental conditions and to cooperatively pass their data through the network to a main location (sink) [1−4]. In last decades, WSNs have been used in many areas, such as air pollution monitoring, health care, water quality monitoring and so on. In WSNs, the sensor nodes are commonly powered by batteries. For some applications where the network is expected to operate for long duration, energy consumption becomes a severe bottleneck and the most important issue in the protocol design as the battery power is limited and replacement is difficult or even impossible [3−5]. Lots of work, such as clustering [6,7], data fusion [8,9] and energy harvesting [10], have been conducted for energy efficiency used in WSNs. We focus on routing in this work.

In WSNs, the transmission range of each sensor node is limited and the sensed data is relayed to the sink node by multiple hops. Lots of routings can exiting simultaneously from one sensor node to the sink node and each node may become one of relay nodes among these routings [2,3]. So how to select relay nodes to compose an energy efficiency routing becomes an important issue for WSNs.

In last decades, genetic algorithms (GA) has been used in main domains, from construction of wind turbines [11] to pattern-recognition systems [1]. GA is an efficient search algorithm that simulates the adaptive evolution process of natural systems. It has been successfully applied to some issues about WSNs, such as optimization of clustering [12], deployment of sensor nodes for coverage [13] and selection of data fusion node [14].

Recently, some researchers have proposed corresponding strategies for optimizing routing by using GA in WSNs. In order to maximize the network lifetime, Babaie S [15] used GA to select routing in WSNs from

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the perspective of power management and energy-efficient communication techniques for each sensor node. Al-Obaidy M [5] applied GA to optimize the communication distance of each sensor node to build an energy efficiency routing for each sensor node. Based on considering the energy model of WSNs, a variable-length chromosomes coding besides selection, crossover and mutation operators in traditional GA is used to select an appropriate routing from sensor node to the sink in [16]. Rong J L [17] proposed a routing optimization method for energy equalization of nodes in WSNs based on multi-objective genetic algorithm. During the process of selecting routing, some factors, such as the energy consumption of routing and the residual energy of nodes, were synthetically considered and a loop circuit detection algorithm is used to detect whether the circuit existed in new chromosome. Long C [18] adopted GA to select suitable node as the cluster head of each cluster to decrease the energy consumption of routing. In [19], a GA technique is employed to find the near-optimal threshold for residual energy below which a node has to give up its role of being the cluster head for selecting suitable cluster head of routing. Meanwhile, some work combined GA with other techniques for energy efficiency routing is WSNs. Zhang H [20] proposed a clustering routing protocol for energy balance of nodes based on Simulated Annealing and GA. Rana K [21] presented energy-efficient routing techniques for WSNs using GA and Particle Swarm Optimization based approach to enhance lifetime of the network. Gupta S K [22] proposed GA based approaches for clustering and routing in WSNs. Su J S [23] proposed a fault-tolerance clustering algorithm with load-balance aware to solve the load unbalance and communication unreliability in WSNs.

The above algorithms have shown that GA can significantly improve the performance of routing in WSNs. However, the fitness function designed in these algorithms only takes less factors into consideration. So the quality of selected routing can be improved greatly. Furthermore, the crossover and mutation operation in these algorithms is operated with all nodes, which is not practical because the transmission range of sensor node is limited and nodes can not communicate with nodes out of their transmission range. So lots of invalid new individuals were generated, which affects the quality of output and performance of GA seriously.

To address the above limitation, we propose a routing optimization scheme based on improved genetic algorithm (ROS_IGA) in this paper. According to the transmission requirement of sensor nodes in WSNs, ROS_IGA improves the crossover and mutation operation to avoid generating unpractical individuals. Moreover, a new fitness function is designed by considering the residual energy of sensor nodes, distance and energy consumption between adjacent nodes, communication delay and relay hops to select suitable routing in ROS_IGA.

The main contributions of this paper are as follows. Firstly, an improved crossover and mutation operation have been proposed to avoid generating unpractical individuals in GA. Secondly, by considering multiple factors, which affects the quality of the selected routing, a new fitness is designed to guide ROS_IGA to find the best routing. Finally, we experimentally evaluate the efficiency of the proposed algorithm. Simulation results show the ROS_IGA can provide better routing than some related competitors.

The rest of this paper is organized as follows. In section 2, we formulate network and routing optimization model used in this work. Then, the ROS_IGA is presented in section 3. The evaluation of our algorithm and the analysis of the obtained results are included in section 4. Finally, we present the main conclusions and future work in section 5.

2. Network and Routing Optimization Model

2.1 Network Model

This work assumed that sensor nodes is distributed uniformly in the monitoring area *MA* with the density ρ as shown in Figure 1, and the sensor network has the following properties:

(1) The network contains large number of homogeneous

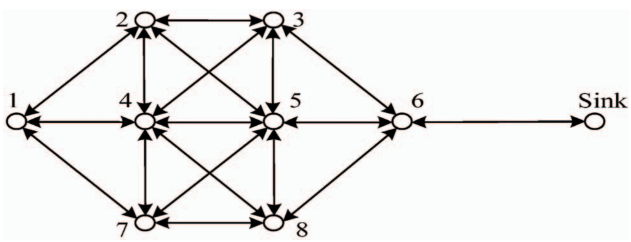

Figure 1. A simple WSNs model.

sensor nodes, and only one sink node located in a fixed position outside the monitoring area. The sensor nodes can't move after deployment generally. Each node has a unique ID number id_i in the system. The number of sensor nodes depends on the size of the application system. To facilitate the description, we suppose the system has N sensor nodes.

(2) The transmission range of all sensor nodes is identical and supposed as R_C. The distance between node i and j is d_{ij}. If and only if $d_{ij} \le R_C$, node i and j can communicate with each other. Then, node i and j are neighbors with each other. NE_i is the neighbor set of node i. All the sensor nodes are deployed by the devices with GPS model, such as robot. So the location and neighbor information of each sensor node is known.

(3) The original energy of each sensor node is same E^{orig} after the sensor nodes deployed and can't be supplemented. The sink node has infinite power supply and significant wireless transmit power. The residual energy of node i ($1 \le i \le N$) after working for a period is E_i^{new}. The energy consumption for wireless sensor nodes sending k bit data to another node that the distance between them is d is [24]:

$$E_{tr} = \begin{cases} k \times E_{elec} + k \times \varepsilon_{fs} \times d^2 & d < d_0 \\ k \times E_{elec} + k \times \varepsilon_{mf} \times d^4 & d \ge d_0 \end{cases} \tag{1}$$

The energy consumption for wireless sensor nodes receiving k bit data is:

$$E_{rs} = k \times E_{elec} \tag{2}$$

where E_{elec} represents the energy consumption for 1 bit data to do the dispose like coded modulation and so on. ε_{fs} and ε_{mf} is the propagation loss coefficient. $d_0 = \sqrt{\varepsilon_{fs}/\varepsilon_{mf}}$.

2.2 Routing Optimization Model

The routing optimization model is to select a suitable efficiency path from the multiple routings for one sensor node to the sink [25]. For a WSNs system with N sensor nodes, the number of possible routings from one sensor node to the sink is $p(N) = 2^{N-1} - N + 1$. So selecting a suitable routing is essential for the WSNs system. A large amount of computing resources and energy will be consumed if the traditional method is adopted for selecting a suitable routing from these possible routings. So the intelligence heuristic method is needed. Genetic algorithm, which simulates "the survival of the fittest" in natural evolution, can effectively solve the large-scale complicated optimization problem. As mentioned in section 1, lots of works have been conducted by adopting GA method for routing optimization in WSNs. So we adopt the improved GA to select routing in this work.

3. ROS_IGA

3.1 Main Idea

Each individual in the GA population represents a possible solution to the problem. Finding individuals which are the best suggestions to the optimization problem and combine these individuals into new individuals is an important stage of the evolutionary process. Using this method repeatedly, the population will hopefully evolve good solutions. Specifically, the operations in GA are: selection (according to some measure of fitness), crossover (a method of reproduction, "mating" the individuals into new individuals), and mutation (adding a bit of random noise to the off-spring, changing their" genes").

Although many researchers have adopted GA for routing optimization in WSNs, the crossover as well as mutation operation did not consider the network topology of WSNs. As a result, lots of invalid individuals are generated, which greatly decrease the efficiency of GA. For example, a routing "$1 \to 2 \to 8 \to 6 \to$ sink" can be generated after crossover and mutation operation by these methods. However, this routing is unpractical because $NE_2 = \{1, 3, 4, 5\}$ and $8 \notin NE_2$. In other words, the node id_2 can not communicate with the node id_8 directly.

In this work, we propose ROS_IGA for routing optimization in WSNs. Based on the location information got during the deployment of sensor nodes, the ROS_IGA take the genes of chromosomes before and after crossover and mutation point into consideration during the evolution to make generating practical individuals. Moreover, the accumulated distance, energy consumption between adjacent nodes, communication delay and packet relay hops of whole routing besides the remainder available energy of nodes is considered for designing the fitness function of GA in this work, which guide the proposed algorithm to find suitable routing. The details of ROS_IGA are expressed as follows.

3.2 Individual Representations

To solve an optimization problem with GA, one need to encode the candidate solution to the underlying problem into a vector form, then the evolved vector is decoded to the solution form to evaluate its merit of fitness. In our work, the detail of individual representations is expressed as follows:

(1) According to the topology of WSNs, we take the variable-length chromosomes coding, which is widely used [5,16], to form practical individual.

(2) The genes in each individual are indicated by the corresponding node's ID. So the routing of one sensor node to the sink is formed by the set of nodes' ID.

(3) Each ID can only used one time in each individual to avoid the loop circuit.

3.3 Fitness Function

In GA, the fitness function is used to judge the quality of chromosomes, guide the evolutionary process and select the final output. So designing a suitable fitness function is essential to the performance of GA. To facilitate the description, we take $P(id_i, s)$ and $p_j(id_i, s)$ is all possible individuals and an individual (routing) from node id_i to the sink, respectively and id_l is one of relay node in $p_j(id_i, s)$. E and e is the set of all relay edges in $P(id_i, s)$ and one all relay edge in $p_j(id_i, s)$, respectively.

The factors affecting the choice of individual $p_j(id_i, s)$ include: (1) the remainder available energy function of each node, $rene(id_l)$, (2) distance function of the edge between adjacent nodes, $dist(e)$, (3) energy consumption function of the edge between adjacent nodes, $ene(e)$, (4) communication delay function of the node, $delay(id_l)$, (5) packet relay hops of each routing, $hop(p_j(id_i, s))$. Then, these parameters can determine the affinity function of $p_j(id_i, s)$, $f(p_j(id_i, s))$

$$f(p_j(id_i,s)) = \frac{\sum_{v_l \in p_j(id_i,s)} rene(id_l)}{\omega_1 f_1 + \omega_2 f_2 + \omega_3 f_3 + \omega_4 f_4} \tag{3}$$

$$f_1 = \frac{\sum_{e \in p_j(id_i,s)} dist(e)}{\sum_{e \in E} dist(e)} \tag{4}$$

$$f_2 = \frac{\sum_{e \in p_j(id_i,s)} ene(e)}{\sum_{e \in E} ene(e)} \tag{5}$$

$$f_3 = \frac{\sum_{id_l \in p_j(id_i,s)} delay(id_l)}{\sum_{id_l \in P(id_i,s)} delay(id_l)} \tag{6}$$

$$f_4 = \frac{hop(p_j(id_i,s))}{\sum hop(P(id_i,s)} \tag{7}$$

where f_1 is the distance of the edges of $p_j(id_i, s)$ versus the distance of all the edges in the $P(id_i, s)$, f_2 is the ratio of the energy consumed by the edges of $p_j(id_i, s)$ and the energy consumed by all the edges in the $P(id_i, s)$, f_3 is the delay of the edges in $p_j(id_i, s)$ versus the delay of all the nodes in the $P(id_i, s)$, and f_4 is the ratio of the hop of $p_j(id_i, s)$ and the hop of all individuals in $P(id_i, s)$. ω_1, ω_2, ω_3 and ω_4 are the weight of effective energy, delay and distance constraints in the fitness function, and $\omega_1 + \omega_2 + \omega_3 + \omega_4 = 1$. We set $\omega_1 = 0.4$, $\omega_2 = 0.2$, $\omega_3 = 0.2$ and $\omega_4 = 0.2$. The higher fitness value indicates the more suitable path.

3.4 Selection

The scheme of elitism preservation and roulette is used to select the individuals for the next generation. Firstly, we select 50% individuals with better fitness value as the elitism for propagating to the next generation. Then, we used the roulette strategy to generate the other individuals for the next generation.

3.5 Crossover and Mutation

The crossover and mutation operation in [15–23] is operated in the whole range, which is not practical for WSNs because the sensor node's transmission range is limited and nodes can not communicate with nodes out of their transmission range. This unreasonable operation brings seriously impact on the output and rate of convergence of GA. So we improve the crossover and mutation operation in this work and the detail is as follows.

Suppose p_j (id_i, s) and p_k (id_i, s) are two individuals used for crossover and mutation. id_c and id_m is the crossover and mutation point, respectively. And id_c^b, id_m^b and id_m^a is the gene before (precedent) the crossover gene, before the mutation gene and after (succeed) the mutation gene, respectively. The comparison about the related works and the proposed crossover and mutation operation in this work is shown in Table 1 and the pseudo-code of improved crossover and mutation is shown in Algorithm 1.

For the crossover operation, the algorithm checks the information of crossover point and its precedent. If the crossover point of one individual is the same gene with the other individual (line 2–3) or belong to the neighbor set of the corresponding precedent in other individual (line 4–5), the crossover is conducted. Otherwise, the operation is discarded (line 6–7). For the mutation operation, the algorithm checks the neighbor sets of the precedent and succeed gene of mutation point. It selects the gene belong to both the neighbor sets of the precedent and succeed gene to replace the mutation gene (line 10–15). With the improved crossover and mutation operation, the generated individual can satisfy the transmission requirement.

Algorithm 1. Improved crossover and mutation operation
Input: individuals before crossover and mutation
Output: individuals after crossover and mutation
// the crossover operation
1: **for** (each pair of individuals)
2: **if** ($p_j\_id_c^b == p_k\_id_c^b$)
3: take crossover of p_j and p_k;
4: **elseif** (($p_j\_id_c \in NE(p_k\_id_c^b)$) & ($p_k\_id_c \in NE(p_j\_id_c^b)$))
5: take crossover of p_j and p_k;
6: **else**
7: don't take crossover of p_j and p_k;
8: **endif**
9: **endfor**
// the mutation operation
10: **for** (each individual)
11: **if** ($id_n \in (NE_{id_m^b} \cap NE_{id_m^a})$)
12: take id_n to repalce id_m;
13: **else**
14: don't take mutation;
15: **endif**
16: **endfor**

4. Performance Evaluation

4.1 Experiment Setup

To evaluate the performance of ROS_IGA, we carried out a corresponding simulation under MATLAB R2010a and compared the simulation results with the protocols of Flooding and the algorithm proposed in [15] (call Ref15 for short later). The simulation is constructed on Professional MS Windows 7 with Intel (R) Core (TM) i5-3470 processor (3.2 GHz) and 4 GB RAM. In our simulation, each sensor node has the ability of data fusion and the capacity of packet after data fusion is uniform. We only consider the energy used for data transmission and ignore the energy caused by data fusion. The parameters for simulation are shown in Table 2.

Table 2. The parameters for simulation

Parameter	Value
Rang of WSNs	(0, 0) to (200, 200)
Location of sink	(200, 200)
Number of sensors nodes (N)	200
Original energy of sensor node	2J
Length of packet	400 byte
E_{elec}	50 nJ/bit
ε_{fs}	10 pJ/(bit · m^2)
ε_{mf}	0.0013 pJ/(bit · m^4)
Crossover probability P_e	0.8
Mutation probability P_m	0.1

Table 1. The comparison about the related works and the proposed strategy

	Previous works [15–23]	This work
Crossover	Take the crossover point at anywhere of the individual	Check the crossover point and the neighbor set of its precedent to decide whether taking crossover
Mutation	Take mutation in the whole range of gene	Check the neighbor sets of the precedent and succeed gene of mutation point to decide whether taking mutation

4.2 Evaluation of the Experimental Results

Firstly, we compare the energy consumption for data transmission of these algorithms as shown in Figure 2. We can see that the energy consumption of Flooding is more quickly than Ref15 and ROS_IGA. The reason for this result is that the routing used in Flooding is easy to built but not appropriate, and consumes lots of energy. Both Ref15 and ROS_IGA use GA to find a suitable routing among multiple paths and consider some factors, which affects the quality of routings, into consideration to select the corresponding routing. It can also be observed that the ROS_IGA is better than Ref15. It can be explained by the improved crossover and mutation operation in ROS_IGA, which can find the routing more suitably and quickly.

Then, in order to compare the energy consumption of each round during the run time of WSNs, we select 10 rounds after 100 rounds randomly and compare the variance of energy consumption by these algorithms of each round. The result is shown in Figure 3. We can see that ROS_IGA is better than Ref15 and Flooding. The explanation for this behavior is that more quality factors, such as residual energy of sensor nodes, distance and energy consumption between adjacent nodes, communication delay and relay hops, are considered for the fitness function.

Finally, we compare the lifetime of WSNs of these algorithms as shown in Figure 4. We can see that the lifetime of WSNs with ROS_IGA is better than that of Flooding and Ref15, which also illustrates the effectiveness of ROS_IGA.

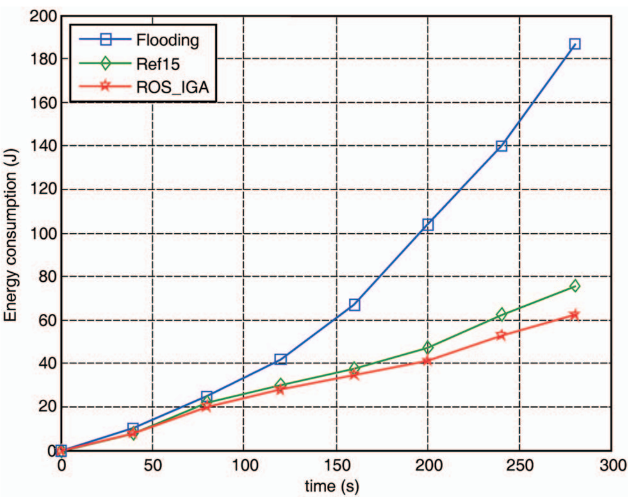

Figure 2. Experimental results of energy consumption.

5. Conclusions

In this paper, we propose a routing optimization scheme based on improved genetic algorithm for WSNs, called ROS_IGA. It adopts variable-length coding to represent chromosome and designs the fitness function by taking the residual energy of sensor nodes, distance and energy consumption between adjacent nodes, communication delay and relay hops as the factors to select suitable routing. Furthermore, the improved crossover and mutation is also designed considering the transmission re-

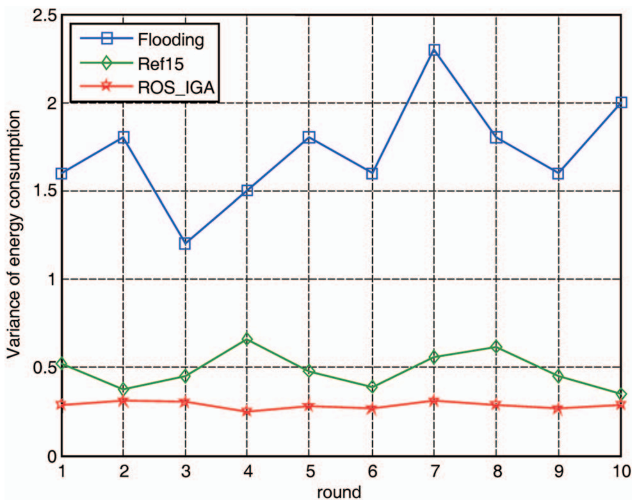

Figure 3. Experimental results of the variance of energy consumption by nodes.

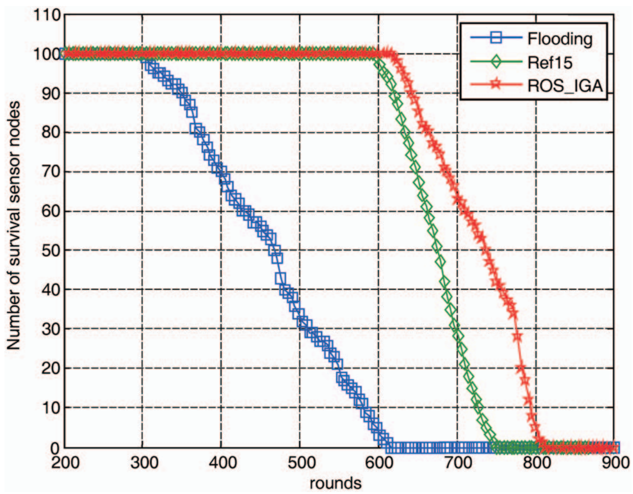

Figure 4. Experimental results of the lifetime with compared algorithms.

quirement of sensor nodes. In order to evaluate ROS_IGA with two other routing techniques, Flooding and Ref15, a series of simulation experiments are conducted. From the simulation results we can conclude that the proposed ROS_IGA can provide better routing than that of Flooding and Ref15.

With the development of electronic technology, energy harvesting device has been added to sensor nodes and the energy of this kind nodes is changed with time. In the future work, we try to build suitable routing for energy harvesting wireless sensor networks.

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