Proposing a New Energy Efficient Routing Protocol for Wireless Sensor Networks

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Summary
Wireless Sensor Networks (WSNs) consist of small nodes with sensing, computing, and Communications capabilities. Development of Wireless Sensor Networks is highly demanded since these networks promise a wide range of potential applications. Their Application domain varies from habitat monitoring to monitor volcanic eruption. There has been a considerable amount of research in developing routing in WSN. In this paper, we proposed a new routing protocol based on Learning Automata. This protocol focuses on fairness of energy consumption and reduction of flooding overhead to increase the network lifetime. We have simulated our protocol and compared its functionality to EBRP and Directed Diffusion routing protocols. Simulation results show that our protocol achieves fairness of energy consumption, reduction of flooding overhead and load balancing across the network.
Key words:
Wireless sensor network (WSN), Learning Automata, Energy consumption, Routing.

1. Introduction

Development of Wireless Sensor Networks are highly demanded since these networks promise a wide range of potential applications in environment detection and monitoring, home automation, forest fire detection, battlefield surveillance, nuclear, urban search and rescue operations.
Recent advances in wireless sensor networks have led to many new protocols specifically designed for sensor networks. Most of the attention, however, has been given to the routing protocols since they might differ depending on the application and network architecture.
There has been a considerable amount of research in developing routing in these networks. Energy saving is one of critical issues for sensor networks since most sensors are equipped with nonrechargeable batteries that have limited lifetime [1].
In this paper, a new routing protocol based on Learning Automata is proposed. Each node in the network is equipped with one learning automata. The learning automaton for each node helps the node to find the next best node for forwarding its packets toward the sink node. This protocol focuses on fairness of energy consumption and reduction of flooding overhead to increase the network lifetime. We have simulated our protocol and compared its functionality to EBRP and Directed Diffusion routing protocols. Simulation results show that our protocol increases the network lifetime and achieves fairness of energy consumption, reduction of flooding overhead and load balancing across the network.
The remaining of this paper is organized as follows. Section 2 gives an overview on related works reported on routing in sensor networks. Learning automata as a basic learning strategy used in the proposed protocol will be discussed in section 3. In section 4 the proposed protocol is presented. Simulation results are given in section 5. Section 6 is the conclusion.

2. Related Work

There are many approaches to routing in sensor networks. Most of them fall into four basic categories: flat routing, hierarchical routing and location-based routing [2]. In flat-based routing, all nodes are typically assigned equal roles or functionality (e.g., SPIN [3], Directed Diffusion [4], Rumor [5], EBRP [6], GBR 7], EAR [8], GEAR [9] and SPEED [10]). In hierarchical-based routing, however, nodes will play different roles in the network (e.g., LEACH [11], TEEN [12], MECN [13], HPAR [14] and GAF [15]). In location-based routing, sensor nodes' positions are exploited to route data in the network (e.g., GAF, GEAR, MECN and SPEED).
In addition to the above, routing protocols can be classified into three categories, namely, proactive, reactive, and hybrid protocols depending on how the source finds a route to the destination [16]. In proactive protocols, all routes are computed before they are really needed, while in reactive protocols, routes are computed on demand. Hybrid protocols use a combination of these two ideas.
In some of these protocols such as Directed diffusion and Rumor routing protocols, the nodes flood the packets to their neighbors and so the traffic on the network is high.
In this paper, we propose a new learning automata based routing protocol that employs learning to decrease the flooding overhead.

Manuscript received February 5, 2010
Manuscript revised February 20, 2010

3. Learning Automat

The automata approach to learning involves determination of an optimal action from a set of allowable actions. Learning Automata is an abstract model which randomly selects one action out of its finite set of action and performs it on a random environment. Environment then evaluates the selected action and responds to the automata with a reinforcement signal. Based on selected action and received signal, the automata updates its internal state and selects its next action. Fig. 1 depicts the relationship between an automaton and its environment.

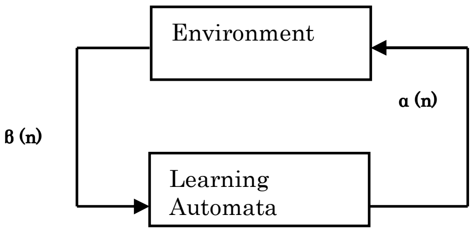

Fig. 1 Relationship between Learning Automaton and its environment

Environment can be defined by the triple E = {α, β, c}, where $\alpha = \{ \alpha_1, \alpha_2, \ldots, \alpha_r \}$ represents a finite input set,
$\beta = \{ \beta_1, \beta_2, \ldots, \beta_r \}$ represent the output set, and
$c = \{ c_1, c_2, \ldots, c_r \}$ is set of penalty probabilities, where each element c_i of c corresponds to one input of action α_i.
An environment in which β can takes only binary value 0 or 1 is referred to as P-model environment. A further generalization of the environment allows finite output sets with more than two elements that take values in the interval [0-1]. Such an environment is referred to as Q-model. Finally, when the output of the environment is a continuous random variable which assumes values in the interval [0, 1], it is referred to as S-model. Learning automata are classified into fixed-structure and variable-structure.
A fixed structure learning automaton is represented by a quintuple $<\alpha, \varphi, \beta, F, G>$ where :
$\alpha = \{ \alpha_1, \alpha_2, \ldots, \alpha_r \}$ is set of actions that it must choose from.
$\Phi = \{ \Phi_1, \Phi_2, \ldots, \Phi_s \}$ is the set of internal states.
β = {0,1} is the set of inputs where 1 represents a penalty and 0 represent a reward.
F: $\Phi \times \beta \rightarrow \Phi$ is a map called the state transition map. It defines the transition of the state of the automaton on receiving an input..
G : $\Phi \rightarrow \alpha$ is the output map and determines the action taken by the automaton if it is in state Φ_j.
A variable-structure learning automaton is defined by the quadruple { α, β, P, T} in which $\alpha = \{ \alpha_1, \alpha_2, \ldots, \alpha_r \}$ represents the action set of the automaton, $\beta = \{ \beta_1, \beta_2, \ldots, \beta_r \}$ represent the input set, and $P = \{ P_1, P_2, \ldots, P_r \}$ represent the action probability set, and finally P(n+1) = T[α(n), β(n), P(n)] represent the learning algorithm. This automaton operates as follows. Based on the action probability set P, automata randomly selects an action αi, and performs it on the environment. After receiving the environment's reinforcement signal, automaton updates its action probability set based on Eq.(1) for favorable responses, and based on Eq.(2) for unfavorable ones.

$$P_i(n+1) = p_i(n) + a.(1-p_i(n)) \tag{1}$$
$$P_j(n+1) = p_j(n) - a.p_j(n) \qquad \forall j \quad j \neq i$$

$$P_i(n+1) = (1-b).p_i(n) \tag{2}$$
$$P_j(n+1) = b / (r-1) + (1-b).p_j(n) \qquad \forall j \quad j \neq i$$

In these two equations, a and b are reward and penalty parameters, respectively. For a=b, learning algorithm is called L_{R-P}, for b<<a, it called $L_{R\varepsilon P}$ and for b=0, it is called L_{R-I}. For more information the reader may refer to [17].

4. The Proposed Protocol

The proposed protocol belongs to flat and reactive routing categories, because whenever a node needs to send a data packet, it takes energy and distance into consideration as two parameters used for selecting the next node to transmit the packet to it. This selection is based on local information and there is no predefined route.
In addition, the nodes in this protocol are assumed stationary.
This protocol is a distributed and scalable protocol in which each node is equipped with a learning automaton. This protocol is consisted of two major phases:

- Identification Phase
- Data Transmission Phase

4.1 Identification Phase

In this phase, each node tries to identify its neighbors and collects information about their residual energy and their distance to the sink node.
Since we assumed that nodes are stationary, the distance measurement between the nodes and the sink is done once. Then each node calculates the average residual energy of its neighbors (E_{avg}) and their average distance to the sink node (D_{avg}). These values are used in the next phase.

4.2 Transmission Phase

In this phase, whenever a node wants to transmit any data toward the sink node, it should choose one of its neighbors in order to transmit data to it. This is done by learning automaton in which all nodes are equipped with. The learning automaton in each node has a number of actions each of which corresponds to one of its neighbors. The selection of each action means to select the neighbor node corresponding to it. At the beginning, probability set of each learning automata is initiated based on Eq.(3):

$$p_i = 1/n \qquad \forall\, i \quad i \le n \qquad (3)$$

As it can be seen in this equation, n denotes the number of neighbors of the node and i denotes the action number of learning automata. At the beginning, the probability of choosing each node is equal, but as time passes, this action probability set is changed and updated. In this way that after choosing a neighbor node for transmitting data to it, its residual energy (E_i) is compared to E_{avg}. Moreover, the distance between this node and the sink node (D_i) is compared to D_{avg}. Then the selected action would be rewarded or penalized with respect to the following four conditions:

• The first condition: if $E_i >= E_{avg}$ and $D_i <= D_{avg}$ then the selected action is rewarded based on Eq.(1) by the amount of a_1 .

• The second condition: if $E_i >= E_{avg}$ and $D_i > D_{avg}$ then the selected action is rewarded based on Eq.(1) by the amount of a_2 .

• The third condition: if $E_i < E_{avg}$ and $D_i <= D_{avg}$ then the selected action is rewarded based on Eq.(1) by the amount of a_3 .

• The fourth condition: if $D_i > D_{avg}$ and $E_i < E_{avg}$ then the selected action is penalized based on Eq.(2) by the amount of b.

To consider the residual energy of nodes and closeness to the sink node simultaneously, the value of a_1 should be greater than a_2 and a_3 , so every node selects one of its neighbors based on these two parameters to transmit data to it. This leads to less participation rate of low energy nodes in routing. Therefore, traffic on each node will be proportional to its residual energy and we would reach to fairness of energy consumption in the network.

As time passes, the first phase should be repeated by each node with the aim to update its information about average residual energy of its neighbors.

5. Simulation Results

In this paper, J-SIM simulator has been used for simulating the proposed protocol. J-SIM is a well-known Java-based simulation environment for numerical analysis [18][19].

It is a scalable, discrete and component based simulator used for wireless networking in an ad-hoc manner.

In this section, the proposed protocol has been compared to EBRP and Directed Diffusion routing protocols. Fairness of energy consumption, residual energy of nodes , network lifetime and overhead ratio has been considered for this comparison. We consider a network of N nodes distributed uniformly and randomly on a 100 ×100 region. In this simulation the IEEE 802.11 communication protocol has been used and sensor nodes and the sink node have been assumed stationary. The sensing rang of all nodes during the simulation was fixed and equaled to 10 meter. Initial energy of each node has been assumed equal to 1 Jules and the required energy for transmitting and receiving packets is equal to 0.003 Jules. Furthermore the packet size is equal to 53 byte. In these simulations, the learning automata with different reward and penalize parameters are employed.

In the simulations, the firs phase should be repeated every 10 second by every node in order to update its neighbors information.

In the first experiment, we assigned different values to reward and penalty parameters of learning automata and then measured the network lifetime. Some of these values are shown in table (1). As you see in this table, when the value of a1 is greater than a2 and a3 the network lifetime is prolonged. It is due to consideration of distance and residual energy of nodes simultaneously.

Table 1: Network lifetime with different values of reward and penalty

a_1	a_2	a_3	b	Lifetime (sec)
0.1	0.2	0.2	0.1	650
0.1	0.1	0.1	0.1	800
0.2	0.1	0.15	0.2	1050
0.2	0.15	0.1	0.2	1100
0.2	0.1	0.1	0.2	1200

According to this simulation, the following values are assumed for reward and penalty in the next simulations.

a_1=0.2 ، a_2=0.1 ، a_3=0.1 and b=0.2

In second experiment, we assumed constant number of nodes equal to 100. We compared the fairness of energy consumption of the proposed protocol to EBRP and Directed Diffusion routing protocols for some duration. Fairness of energy consumption has been calculated using F factor which is introduced in Eq.(4) and its domain is ranging from zero to one. Optimal value of fairness is 1.

$$F = \left(\sum_{i=1}^{n} (E_i)\right)^2 \div \left(n \times \sum_{i=1}^{n} (E_i)^2\right) \qquad (4)$$

The result of this comparison is shown in Fig. 2. As the simulation time elapses, the difference between residual energy of the nodes in the proposed protocol is reduced and the energy is distributed between th enodes more uniformly. This is because of higher probability of choosing the nodes in higher energy level and so, the traffic on nodes with lower energy level will be reduced.

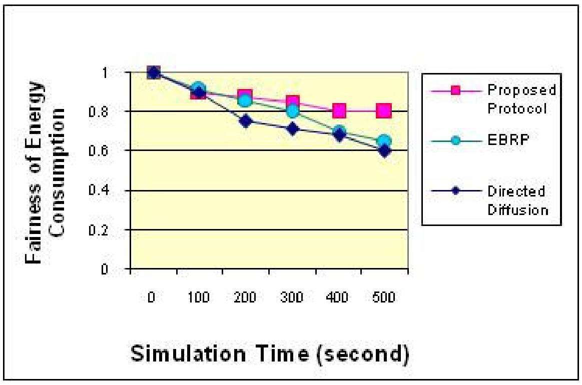

Fig. 2 Change of Fairness of energy consumption with time

In the third experiment, under different number of nodes, the overhead ratio of our protocol is compared to EBRP and Directed Diffusion routing protocols. In this simulation, the overhead ratio is measured based on Eq.(5).

Overhead rate = $PKT_{overhead}$ / ($PKT_{overhead}$ + $PKT_{delivered}$) (5)

In this relation, $PKT_{delivered}$ is the number of packets that are successfully delivered to the destinations and $PKT_{overhead}$ is the number of control packets that are sent in the first phase in order to collect and update neighbors' information..

Fig. 3 depicts the result of this experiment. As you see in this figure, the ratio overhead in the proposed protocol is less than the others. It is due to less flooding in our protocol and more focusing on local information to make decision of selecting the next node in routing.

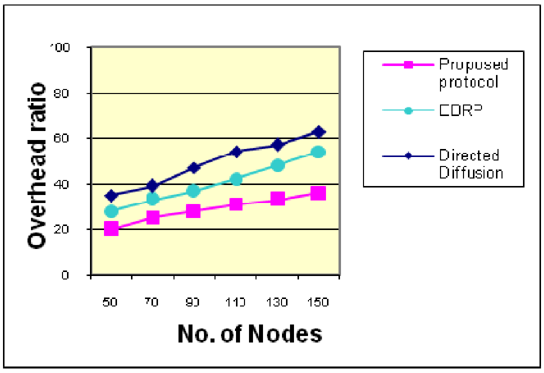

Fig. 3 Overhead ratio Vs Node Density

In fourth experiment, the sum of residual energy of nodes in proposed protocol has been compared to EBRP and Directed Diffusion protocols at different time. Once again, the number of nodes assumed to be equal to 100. As shown in Fig. 4, energy saving in our protocol is better. This is because of lower flooding overhead.

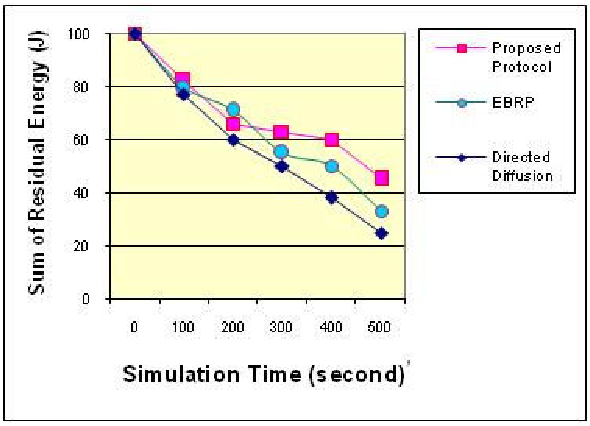

Fig. 4 Comparing sum of residual energy

In the last experiment, by assuming different number of nodes, we compared the network lifetime in the proposed protocol to EBRP and Directed Diffusion routing protocols. Results of this experiment are shown In Fig. 5.

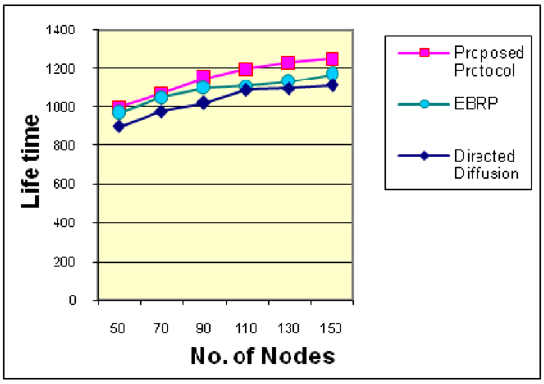

Fig. 5 Lifetime Vs Node Density

In the proposed protocol, by increasing number of nodes, there will be more paths between source node and sink node. Since the traffic on each path is proportional to the residual energy of their nodes, more protection is done for weaker nodes and therefore, the network lifetime will be increased.

6. Conclusion

In this paper, a new distributed routing protocol for sensor networks was proposed which leads to lower flooding overhead, fairness of load balancing across the network and prolonging the network lifetime. The main idea for this protocol was to equip every node with a learning automaton and considering closeness to the sink node and residual energy of nodes simultaneously as two factors for choosing the next node in routing. These results were shown in the simulations and the proposed protocol was compared to EBRP and Directed Diffusion routing Protocols.

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