Ant Colony Optimization-Based Location-Aware Routing for Wireless Sensor Networks

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Abstract. The routing for Wireless Sensor Networks (WSNs) is a key and hard problem, and it is a research topic in the field of WSN applications. Based on Ant Colony Optimization (ACO), this paper proposes a novel adaptive intelligent routing scheme for WSNs. Following the proposed scheme, a high performance routing algorithm for WSNs is designed. The proposed routing scheme is very different from the existing ACO based routing schema for WSNs. On one hand, in the proposed scheme, the search range for an ant to select its next-hop node is limited to a subset of the set of the neighbors of the current node. On the other hand, by fusing the residual energy and the global and local location information of nodes, the new probability transition rules for an ant to select its next-hop node are defined. Compared with other ACO based routing algorithms for WSNs, the proposed routing algorithm has a better network performance on aspects of energy consumption, energy efficiency, and packet delivery latency.

Keywords: WSN, routing, ACO, pheromone, transition probability, simulation.

1 Introduction

1.1 Background

With the rapid growth of modern electronic and wireless communication techniques, wireless sensor networks (WSNs) become more and more effective in many fields, such as battlefield surveillance, biological monitor, smart space, intrusion detection and tracking for temperature, object movement, sound and light [1,2,3,4]. Typically, a WSN consists of a large number of sensors. Each sensor is also called a node, and the nodes have the capability of communicating with each other and the base station (sink node) by multi-hop mode. The sink

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node may be considered as the center for processing data. Each node collaborates with its neighboring nodes in a distributed manner to sense the physical parameters in the environment surrounding this node. Then, as data packets, the nodes process and deliver the sensed data to their neighbors. Some neighbors continue to process and deliver the data packets toward the sink node by the same mode, that is, the multi-hop mode. In WSNs, the energy of nodes is usually provided by micro-batteries with the very limited power. A large number of nodes are usually deployed in the remote, harsh or hostile environment. Hence, it is usually impossible to recharge or replace the batteries of nodes. However, the lifetime of a WSN significantly depends on the batteries of nodes, and a long lifetime is vital in most of WSN applications. Therefore, the energy efficiency routing is a challenge to large-scale WSN applications. In addition, some WSN applications also require a timely data delivery. For instance, when a moving target enters an area of interest, it may be very critical to reduce the delivery delay of the sensed data from the source node (target) to the sink node. If the sensed data is not received by the sink node within a certain acceptable period of time, the sensed data may become useless. Hence, preserving energy efficiency and reducing delivery delay are key issues in the applications of large-scale WNSs. In recent years, more and more attention has been paid to these issues. Due to the limited communication range of nodes, the data packets are delivered from the source node to the sink node through some mediate nodes in a WSN. The routing refers to select an energy-saving and short delivery delay route from the source node to the sink node. Formally, a WSN may be considered as a weighted undirected graph. It is usually a complex combinatorial optimization problem to select a shortest route from the source node to the sink node, while considering many factors, such as energy consumption, packet delivery delay, and energy efficiency, and it has been proved to be an NP-complete problem [4] [8]. Considering the frequent change of the topology of a WSN, the location-aware routing is needed. Due to some new characteristics of large-scale WSNs, such as high density, limited energy and multi-hop communication, the routing becomes very complex. The traditional routing protocols can not satisfy the requirements for WSN applications, especially large-scale WSN applications. Hence, researchers are trying to propose novel routing protocols for WSNs.

Although some routing schemes for WSNs have been proposed based on the graph theory and the greedy search algorithm in the literature [1,2], the high performance routing is still a research topic. Recently, the routing based on Ant Colony Optimization (ACO) has drawn the attention from many researchers [3,4], and the ACO based adaptive routing has shown promising results in solving routing problem [3]. In fact, since the ACO model was proposed by Dorigo [5,6], and it has been successfully applied in solving some complex optimization problems, such as the routing of traffic in busy telecommunication networks, the asymmetric traveling salesman problem, and the graph coloring problem [12]. By using ants as models, we can design soft agents to solve the complex routing problem in large-scale WSNs. Although the capability of each ant is very limited and the cognitive system of each ant is also too simple to acquire the global knowledge of the environment surrounding the ant, the collective behavior of ants emerges a natural model for solving the distributed parallel problem without any extra centralized coordination [5,6].

1.2 Contribution

Our routing scheme is very different from the existing ACO based routing schema for WSNs. Firstly, in our scheme, when an ant is at the node s_i and selects its next-hop node, the search range of the ant is limited to a subset of the set of s_i's neighbors, instead of the total set of s_i's neighbors. On one hand, this guarantees that the data packets are delivered toward the sink node. On the other hand, many useless searches for an ant to select its next hop node are effectively avoided. Secondly, we propose a novel formula to calculate the transition probability with which ants select their next hop nodes. Thirdly, we propose a novel model to determine the amount of the pheromone which an ant will lay on the route traveled by the ant. This diversifies the solutions that ants found, and the probability of the local convergence of the proposed routing algorithm is decreased. In addition, we also propose a novel scheme to evaporate the pheromone on the different segments of a certain route according to the residual energy and the location information of nodes. This also effectively increases the diversity of the solutions found by ants. The simulation results show that the proposed ACO based routing algorithm has a better performance than other ACO based routing algorithms for WSNs [4,7].

The remainder of the paper is organized as follows. In Section 2, the related work is introduced. The novel ACO based routing scheme and the corresponding algorithm for WSNs are proposed in Section 3. The simulation results are presented in Section 4. Section 5 concludes this paper.

2 Related Work

The biological research has shown that ants communicate with each other by sensing the density of pheromone. The pheromone is a chemical substance which ants lay on the routes traveled by themselves. Each ant prefers to moving toward the route with a high density of pheromone. The more the ants which travel a certain route are, the more the accumulated pheromone on this route is, thus the greater the probability with which the other ants select this route is. As a result, the amount of pheromone is gradually increased on this route. However, pheromone may be evaporated over time. Biological experiments have shown that each ant just interacts with the environment surrounding the ant, and independently selects the route without any global knowledge. In the system organized by a group of ants, ants can quickly find the shortest route by sensing the density of pheromone on the routes from the nest to the food node. Inspired by the real ant colony system, Dorigo *et al* [5,6] first proposed artificial ant colony algorithms, namely Ant Colony Optimization (ACO), to solve complex combinatorial optimization problems [12].

The ACO is particularly suitable for large-scale distributed self-organization systems [4]. Recently, the ACO based adaptive routing draws the attention from many researchers [3,4]. Despite that several ACO based routing algorithms for WSNs have been proposed, those algorithms are based on the framework proposed by Dorigo [5,6]. In fact, the core idea of ACO based routing lies in two key points. One is to define the formula to calculate the transition probability with which an ant selects its next-hop node, and the other is to determine the rules used to update the pheromone on the routes. According to different WSN applications, researchers defined the different formula to calculate the transition probability, and modified the rules to update the amount of pheromone. In this paper, we define a novel formula to calculate the transition probability under the framework of the ACO based routing proposed by Dorigo, and we also define novel rules to update the amount of pheromone on the routes. Following the proposed scheme, we design a new ACO based routing algorithm for WSNs. Simulation results show that the proposed algorithm has a better comprehensive performance than other ACO based routing algorithms for WSNs [4,7].

3 ACO Based Location-Aware Routing for WSNs

3.1 Problem Description

A WSN consists of m static and identical wireless sensors. Each sensor is called a node. The nodes are uniformly distributed in a flat region, as shown in Fig.1. The nodes are equipped with omni-directional antennas, and the communication range of each node is a circle area whose radius is r. A WSN is formally described as a weighted undirected graph $G(V, E, L)$. Here, V=$\{s_1, s_2, ..., s_m\}$, and each $s_i \in V$ represents a sensor node in a WSN. E is the set of edges, L is the

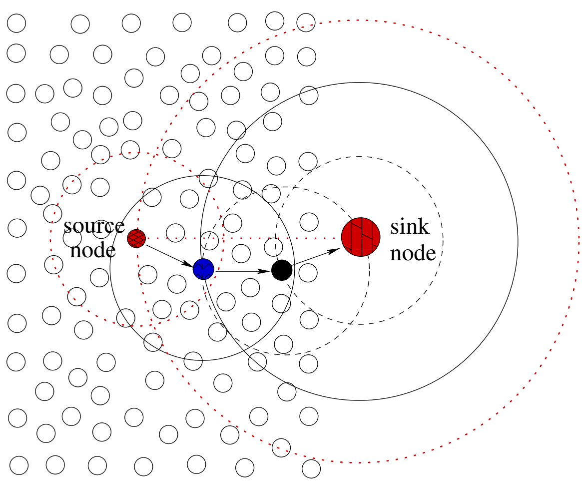

Fig. 1. Ant colony optimization-based location-ware routing for WSNs

set of weights, and $E \subset V \times V \times L$. At any instant t, for any $s_i, s_j \in V$, $i \neq j$, the locations of s_i and s_j are denoted as (x_i, y_i) and (x_j, y_j), respectively. The distance between s_i and s_j is denoted as d_{ij}, and d_{ij} is calculated by the following formula.

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \ . \tag{1}$$

For any $s_i, s_j \in V$, if $d_{ij} \leq r$, and s_i and s_j both are active, that is, s_i and s_j both are working, then there is an undirected edge $(s_i,\ s_j,\ \psi_{ij}(t)) \in E$. Here, the weight $\psi_{ij}(t) \in [0, 1]$ is the cost to deliver a data packet from s_i to s_j at instant t. For any $s_i \in V$, the residual energy of s_i is denoted as $e_i(t)$ at instant t. Traditionally, the set of s_i's neighbors is defined as follows.

$$N(s_i) = \{s_j \mid s_j \in V, d_{ij} \leq r\} \ . \tag{2}$$

In this paper, s_0 is the source node, and s_b is the sink node. The set of s_i's next-hop neighbors is defined as follows.

$$C(s_i) = \{s_j \mid s_j \in N(s_i), d_{jb} \leq d_{ib}\} \ . \tag{3}$$

The problem to be solved is to find the best optimal route from the source node s_0 to the sink node s_b, such that a given data packet may be delivered from s_0 to s_b, while energy consumption is minimized and packet delivery latency is minimized. This is a hard combinatorial optimization problem. As shown in Fig. 1, before a given data packet is delivered from the source node to the sink node, we need to find the best optimal route from the source node to the sink node. In this paper, we propose a novel ACO based routing algorithm to effectively solve this problem.

3.2 The Basic Principal of ACO

In the following, the basic principal of ACO is introduced based on the practical procedure that ants find food. Similar to [3], suppose that there are three ants a_1, a_2 and a_3 at the nest node (source node) s_0, and that there are three routes ϕ_1, ϕ_2 and ϕ_3 from the nest node s_0 to the food node (sink node) s_b. The length of ϕ_1 is greater than the length of ϕ_3 and the length of ϕ_3 is greater than the length of ϕ_2. The route ϕ_1 includes four nodes s_0, s_1, s_2 and s_b, the route ϕ_2 includes three nodes s_0, s_3 and s_b, and the route ϕ_3 includes five nodes s_0, s_4, s_5, s_6 and s_b. Here, it is noted that the number of the nodes included in a route is not generally related to the length of the route.

The procedure for ants to find the shortest route from s_0 to s_b is described as follows. Initially, at s_0, the three ants have no knowledge about the routes from s_0 to s_b. Each ant selects one of the three routes in a random mode. Suppose that a_1 selects ϕ_1, a_2 selects ϕ_2 and a_3 selects ϕ_3, and that the three ants move at the same speed. At the initial instant t_0, the three ants start to move from s_0 to s_b along the three routes. Clearly, due to the shorter length of ϕ_2, a_2 first reaches s_b, then a_3 reaches s_b, and a_1 finally reaches s_b. Once an ant reaches

s_b, the ant immediately returns toward s_0 along the route from which the ant just comes. While returning, the ants will lay a different amount of pheromone on the route traveled by themselves. At instant t, the pheromone on the route from s_i to s_j is denoted as $\psi_{ij}(t)$, here s_i and s_j are two neighboring nodes. The pheromone which the ant k lays on the route from s_i to s_j is denoted as $\Delta\psi^k_{ij}(t)$. If the ant k does not pass the route from s_i to s_j, then $\Delta\psi^k_{ij}(t)$ is equal to 0. Usually, the value of $\Delta\psi^k_{ij}(t)$ is inversely proportional to the length of the route traveled by the ant k from s_0 to s_b. Let the length of the route found by the ant k be L^k at instant t. When a_2 return to s_0 before a_1 and a_3, the value of $\psi_{03}(t)$ is immediately set to $1/L^2$. Similarly, when a_3 return to s_0 before a_1, the value of $\psi_{04}(t)$ is immediately set to $1/L^3$. When a_1 return to s_0, the value of $\psi_{01}(t)$ is immediately set to $1/L^1$. When all the three ants return to s_0, we say that these ants complete a round travel. Next, the ants start the second round travel. At s_0, the ants prefer to choosing the route with a high density of pheromone. Since $1/L^2 > 1/L^3 > 1/L^1$, ϕ_2 is chosen by the ants. When the ants complete the second round travel, the density of pheromone on ϕ_2 is much greater than that on ϕ_1 or ϕ_2. Hence, ϕ_2 is the shortest route from s_0 to s_b.

In the above example, any ant at s_0 will be able to choose the optimal route once other ants return to s_0. If the ant k is at s_i, and there is no pheromone on any route from s_i to s_i's next-hop neighbors, the ant k makes a random decision to select one route with the probability of 0.5. However, when there is pheromone on routes, the ant k will select the route with a higher density of pheromone. It is noted that there are other types of ants that use pheromone to communicate with each other in different modes. Hence, there are still other ACO approaches [3]. In addition, the pheromone on a route may be evaporated over time. According to the different problems, different rules to lay or evaporate pheromone are defined to effectively solve these different problems.

3.3 The Proposed Routing Scheme for WSNs

To select the best optimal route from the source node to the sink node, suppose that each node in a WSN has a memory block in which the residual energy of the node and its neighbors, the location information of the node, its neighbors and the sink node are stored. Each ant is a mobile agent that has a contraindication list to memory the nodes traversed by the ant in a round travel. The contraindication list may help each ant avoiding to select the nodes which have been traversed by the ant. Furthermore, each ant may avoid to cycle on the same route. In addition, when the ant k is at s_i at instant t, the ant k will select the node $s_j \in C(s_i)$ as the next-hop node in a probability mode, as shown in Fig. 2. We believe that the location information of nodes significantly influences the probabilities with which the ant k selects s_j as the next-hop node. Hence, we define the location function ξ_{ij} as follows.

$$\xi_{ij} = \left(\frac{d_{0b}}{d_{0i} + d_{ij} + d_{jb}}\right) \times \left(1 - \frac{d_{ij}}{\sum\limits_{s_l \in C(s_i)} d_{il}}\right) \quad . \tag{4}$$

Where d_{ij} is the distance from s_i to s_j, d_{0b} is the distance from s_0 to s_b, d_{0i} is the distance from s_0 to s_i, and d_{jb} is the distance from s_j to s_b. Clearly, $0 \leq \xi_{ij} \leq 1$. The greater the value of ξ_{ij} is, the greater the probability with which ants select s_j as the next-hop node is. If there is not any next-hop neighbor to select, that is, $C(s_i)\backslash\{s_i\}$ is empty, then the ant k returns to the previous-hop node of s_i. Let the previous-hop node of s_i be s_l. Before the ant k makes a reselection at s_l, s_i is added to the contraindication list of the ant k, so that the ant k does not select s_i as the next-hop node again.

In addition, we believe that the residual energy of nodes influences the probabilities with which the ant k selects s_j as the next-hop node. Therefore, we define the energy function $\eta_{ij}(t)$ as follows.

$$\eta_{ij}(t) = \frac{e_j(t)}{\sum\limits_{s_l \in C(s_i)} e_l(t)} \quad . \tag{5}$$

Where $e_l(t)$ is the residual energy of s_l at instant t. The greater the value of $\eta_{ij}(t)$ is, the greater the probability with which the ant k selects s_j as the next-hop node is. To comprehensively consider the location information and the residual energy of nodes, we define the novel transition probability with which the ant k at the node s_i selects $s_j \in C(s_i)$ as the next-hop node at instant t as follows.

$$p_{ij}^k(t) = \frac{[\psi_{ij}(t)]^\alpha \times [\xi_{ij}]^\beta \times [\eta_{ij}(t)]^\gamma}{\sum\limits_{s_l \in C(s_i)} [\psi_{il}(t)]^\alpha \times [\xi_{il}]^\beta \times [\eta_{il}(t)]^\gamma} \quad . \tag{6}$$

Where α, β and γ are the adjustable weights of $\psi_{ij}(t)$, ξ_{ij} and $\eta_{ij}(t)$, respectively. Hence, the routing selection of ants may be tuned according to the different values of α, β and γ. A higher value of α increases the chance for ants to choose the route with a higher pheromone, a higher value of β increases the chance for ants to choose the route with a shorter length, and a higher value of γ increases the chance for ants to choose the node with more residual energy. In general, different values of α, β and γ are selected for different situations. When a WSN is not stable, a lower value of α is generally preferred. This is because the pheromone on a route may not necessarily reflect the optimality of the route at that time. As a WSN becomes stable, a higher value of α is preferred. If a lower latency of packet delivery is needed, a higher value of β is preferred. This is because a higher value of β means a shorter route to select. When the energy of nodes is not uniformly distributed, a lower value of γ is generally preferred. In fact, it may improve the performance of ants' cooperative routing to dynamically change the values of α, β and γ [3].

For each ant, it starts to move from s_0 to s_b. When the ant k reaches s_b, the ant k finds a route R^k from s_0 to s_b. Suppose R^k includes the nodes s_0, s_i, s_j and s_b, denoted as $R^k(s_0, s_i, s_j, s_b)$. Then, the ant k immediately starts to return to s_0 from s_b along the route R^k. While returning, the ant k orderly updates the pheromone ψ_{jb}, ψ_{ij} and ψ_{0i}. Suppose that there are n ants in a WSN. We call it a round travel that n ants reach s_b from s_0, and then return to s_0 from s_b along the routes from which the ants just come, respectively. Suppose that it takes a unit time for ants to finish a round travel. The rule used for updating the pheromone on the route R_{ij} (the segment between s_i and s_j) is defined as follows.

$$\psi_{ij}(t+1) = (1-\rho(t)) \times \psi_{ij}(t) + \Delta\psi_{ij} \quad . \tag{7}$$

Where $\rho(t)$ is the pheromone evaporating rate at instant t, and $0 \le \rho(t) \le 1$. $\rho(t)$ is calculated by the following formula.

$$\rho(t) = (1-\eta_{ij}(t)) \times (1-\xi_{ij}) \quad . \tag{8}$$

The above formula implies that the pheromone evaporating rate $\rho(t)$ is a function of the residual energy and the location information of nodes, instead of a constant. This scheme has a better adaptivity to the frequent change of the topology of a WSN. In Formula (7), $\Delta\psi_{ij}$ is the pheromone increment on the route between s_i and s_j in the current round travel. $\Delta\psi_{ij}$ is calculated by the following formula.

$$\Delta\psi_{ij} = \sum_{k=1}^{n} \Delta\psi_{ij}^{k} \quad . \tag{9}$$

Where $\Delta\psi_{ij}^{k}$ is the pheromone that the ant k laid on the route between s_i and s_j in the current round travel. $\Delta\psi_{ij}^{k}$ is calculated by the following formula.

$$\Delta\psi_{ij}^{k} = \begin{cases} \frac{d_{0b} \times Q}{(d_{0i}+d_{ij}+d_{jb})L^k} & \text{if ant } k \text{ passed from } s_i \rightarrow s_j \\ 0 & \text{otherwise} \end{cases} \quad . \tag{10}$$

Where Q is a constant, d_{0i}, d_{0b}, d_{ij} and d_{jb} have the same meaning as that of Formula (4), respectively. L^k is the length of the route that is found by the ant k in the current round travel.

3.4 The Proposed Routing Algorithm for WSNs

Our algorithm (ACLR) is composed of two phases. In the first phase, for each ant k, following the proposed routing scheme, the ant k starts to look for an optimal route from the source node s_0 to the sink node s_b. When the ant k reaches the sink node s_b, a route R^k from the source node to the sink node is found by the ant k. Let the length of R^k be L^k. In the second phase, each ant k returns to the source node from the sink node along the route R^k. At the meantime, following the proposed pheromone updating rules, the ant k updates the pheromone on each segment of R^k. Let the total number of ants be n, and the total number of nodes in a WSN be m. num is the number of the round travels which the ants complete in finding optimal routes. Γ^k is the contraindication list of the ant k at instant t. The ACLR is described as follows.

Initialize the numbers n,num of ants and round travels, $\psi_{ij}(0)$, and $t \Leftarrow 0$
while the end iteration condition is not met **do**
  $t \Leftarrow t + 1$
  for $k = 1$ to n **do**
    Ant k is positioned on the source node s_0
    $s_i \Leftarrow s_0$; $R^k \Leftarrow \varnothing$; $\Gamma^k \Leftarrow \varnothing$
    while $s_i \neq s_b$ **do**
      if $C(s_i) - \Gamma^k \neq \varnothing$ **then**
        Select s_j from $C(s_i) - \Gamma^k$ to move according to the probabilistic transition rules
        $R^k \Leftarrow R^k \cup \{s_i\}$; $\Gamma^k \Leftarrow \Gamma^k \cup \{s_i\}$; $i \Leftarrow j$
      else
        Return to the previous-hop of s_i; $\Gamma^k \Leftarrow \Gamma^k \cup \{s_j\}$
      end if
    end while
    Compute the length L^k of R^k by Formula (1)
    Calculate $\Delta\psi_{ij}^k$ by Formula (10), here (s_i, s_j) is a segment of R^k
  end for
  Update the pheromone $\psi_{ij}(t)$ by Formula (7)-(10)
  Compare and update the best solution set
end while
Return(the best optimal solutions)
End.

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4 Simulation Results

Through simulations, we compare the proposed algorithm (ACLR) with the following four algorithms: Basic Ant Routing (BAR), Sensor-driven Cost-aware Ant Routing (SCAR), Flooded Piggybacked Ant Routing (FPAR) [7], and the IAR [4], which are classical ACO based routing algorithms for WSNs. For different algorithms, we mainly compare energy consumption, packet transmission delay and energy efficiency.

4.1 Simulation Environment

The simulations were conducted with the network simulation software OPNET to evaluate the performance of algorithms. We compare ACLR with BAR, SCAR, FPAR and IAR. The network area is set to 200×300 (m^2), 10000 sensors are uniformly deployed in this region, and the wireless communication radius of sensors is 30m. The data rate at MAC layer is 2Mbps. $\alpha = 3, \beta = 3, \gamma = 3$, and Q=100J. For any node s_i, suppose that s_j is any next-hop node of s_i. The initial pheromone on the route between s_i and s_j is set to $\psi_{ij}(0)$=0.01. The total number of ants are 20.

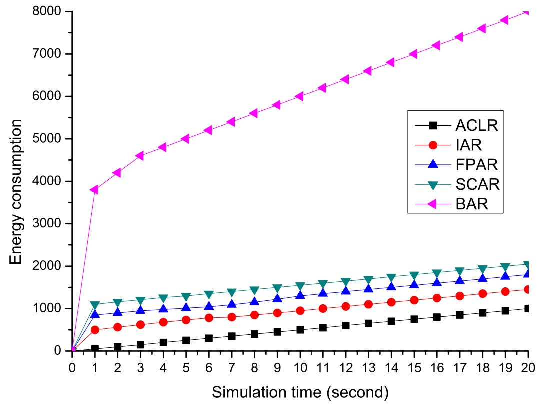

Fig. 2. Energy consumption of different algorithms

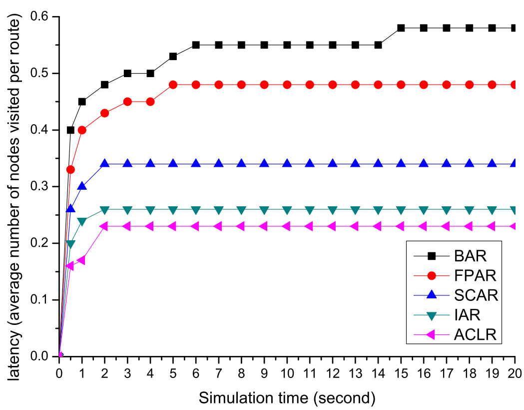

Fig. 3. Packet delivery latency of different algorithms

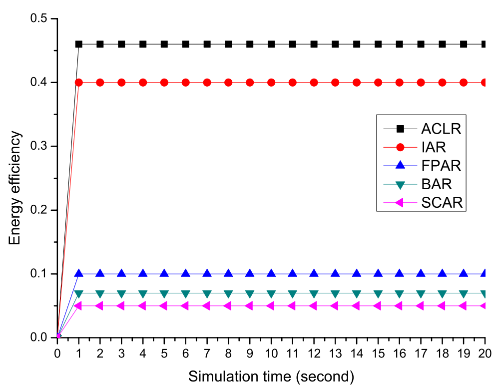

Fig. 4. Energy efficiency of different algorithms

For each case, by randomly choosing the locations of the source node, we simulate each algorithm 50 times so as to get the average results.

4.2 Energy Consumption

Energy consumption refers to the used energy in the process of data packet delivery. Similar to [4], we assume that it consumes one unit energy to directly deliver a data packet between two nodes. Hence, the total energy consumption may be defined as the total number of the data packets which are directly sent between nodes. Fig.2 shows that the energy consumption of ACLR is the smallest. The main reason is that, for ACLR, the least number of redundant data packets are delivered. Therefore, the least amount of energy is consumed.

4.3 Packet Delivery Latency

The packet delivery delay refers to the used time to transmit a data packet from the source node to the sink node, that is, end-to-end delay. For each data packet, suppose that the total time for each node to receive, process and send a data packet is uniform. Since the delay time when a data packet is in a wireless channel is much smaller than the time for a node to receive, process and send the data packet, the delay time when the data packet is delivered in a wireless channel may be neglected. Furthermore, we can use the average number of the nodes included in a route to estimate the data packet delay time in different algorithms [4]. Fig.3 shows that the data packet delivery delay of ACLR is smallest.

4.4 Energy Efficiency

In a WSN, energy efficiency refers to the ratio of the number of data packets received at the sink node by the total consumed energy [9]. A higher energy efficiency means that a specific WSN has a better energy-saving feature. Fig.4 shows that ACLR has the highest energy efficiency among all the five algorithms. We believe that the main reason is the search range of ants is effectively limited in ACLR.

5 Conclusion

The routing for WSNs has been a topic in the field of WSN applications for a long time. In this paper, we proposed a novel routing scheme for WSNs based on Ant Colony Optimization (ACO). We define a novel formula to calculate the transition probability with which an ant selects its next-hop node, and we also propose some novel rules to update the pheromone on the routes traveled by ants. By defining the transition probability as a function of the location information of nodes, the residual energy of nodes and the pheromone on routes, we effectively achieve the balance between node energy and packet transmission delay. Moreover, we define the pheromone evaporating rate as a function of the residual energy and location information of nodes to overcome the disadvantage that the constant rate of pheromone evaporating poses. The simulation results show that the proposed algorithm has a better performance than that of BAR, SCAR, FPAR proposed in [7], and IAR proposed in [4].

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