

Biologically Inspired Cooperative Routing for Wireless Mobile Sensor Networks

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Abstract—Biological systems present remarkable adaptation, reliability, and robustness in various environments, even under hostility. Most of them are controlled by the individuals in a distributed and self-organized way. These biological mechanisms provide useful resources for designing the dynamical and adaptive routing schemes of wireless mobile sensor networks, in which the individual nodes should ideally operate without central control. This paper investigates crucial biologically inspired mechanisms and the associated techniques for resolving routing in wireless sensor networks, including Ant-based and genetic approaches. Furthermore, the principal contributions of this paper are as follows. We present a mathematical theory of the biological computations in the context of sensor networks; we further present a generalized routing framework in sensor networks by diffusing different modes of biological computations using Ant-based and genetic approaches; finally, an overview of several emerging research directions are addressed within the new biologically computational framework.

Index Terms—Adaptive routing, *ad hoc* networks, ant-based routing, ant colony optimization, biological computing, dynamic routing table, genetic approach, sensor networks.

I. INTRODUCTION

THE MANUFACTURING of small and low-cost sensors has become economically feasible due to modern electronic fabrication techniques. These sensors measure the physical parameters in the environment surrounding them and then transform these acquired measurements into the signals which can be processed to characterize the local phenomena associated with the surroundings. Nowadays, a large number of sensors are deployed wirelessly; hence, a wireless sensor network (WSN) with communication capabilities plays an important role. There are various applications of WSN. For example, the WSNs have ubiquitous military and civil applications such as *target field*

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imaging, intrusion detection, weather monitoring, security and tactical surveillance, distributed computing, ambient conditions tracking for temperature, object movement, sound, light, inventory control, and disaster management. Typically, WSNs consist of hundreds or thousands of sensor nodes, and these sensor nodes usually possess the capability of communicating with the centralized sensor base station (BS) and each other. Since the coverage of the individual sensors is geographically confined, a greater number of sensors are often deployed to increase the coverage region for the sensing accuracy.

Iyengar *et al.* recently explored several new routing schemes for wireless sensor networks [1]–[10]. To broadcast the sensed information among a WSN, usually a low-cost and fast routing method is needed. Resource- and robustness-constrained routing has been introduced in [2]–[4], [6], [7], and [10]. Graph theory and greedy search algorithm have been adopted in [1], [8], and [9]. Adaptive routing has been discussed in [5]. However, those classical routing methods are employed by a sensor node or a base station independently. More recently, *biologically-inspired cooperative routing* has begun to draw attention from many researchers [11], [12].

Many desirable characteristics, such as scalability and robustness, are exhibited in biological systems despite of individual simplicity, wherein the *global complex structures* are typically flexible to adapt to a new environment and are robust to resist occasional individual failures. For individuals, their behavioral capabilities are limited and their cognitive systems are not powerful enough to acquire global knowledge. The collective behavior of biological species (e.g., ants) provide a natural model for distributive problem solving without any extra central control or coordination. The bottleneck of the current biologically-inspired research is to investigate how the collective complexity arises from the individual simplicity. Studies have shown that *self-organization* and *stigmergy* are two key ideas in swarm systems [13], [14]. The basic concepts of self-organization include *positive feedback, negative feedback, fluctuation amplification, and multiple interactions*.

Consider the *ant colony* as an example to illustrate these concepts: the action of disposing pheromone is a positive feedback mechanism to recruit more ants such that more pheromones are disposed on the shorter path; however, the evaporation of pheromone is a negative feedback to reduce the pheromone level; in this way, the shortest paths to the food source can be found accordingly. Moreover, stigmergy is defined as the *indirect communication* used by ants in nature to coordinate their joint problem solving activities. Ants achieve stigmergic communication by laying a chemical substance called *pheromone* [15], [16] that induces changes in the environment which can

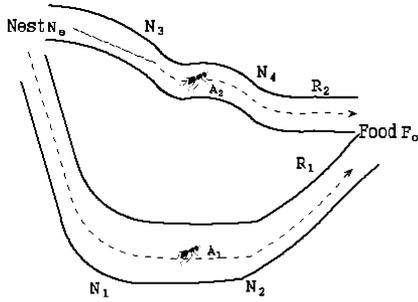


Fig. 1. Example of ACO.

be sensed by other ants. In recent years, computer scientists were able to transform the models of *collective intelligence* of ants into the useful optimization and control algorithms [13], [17]–[20]. For example, in the interesting and emerging field of *ant colony optimization* (ACO) [15], [17], [18], [21]–[23] a colony of ants is typically modeled as a society of mobile agents [24]–[27]. ACO has been applied in many combinatorial optimization problems such as the *asymmetric traveling salesman problem* [28], [29], *graph coloring problem* [30], and *vehicle routing problem* [15]. In this paper, we will discuss how ACO can be adopted for the efficient and robust routing for wireless mobile sensor networks. First, we will focus on the ACO approaches in network routing; for instance, the *genetic algorithm* (GA) is a typical biologically-inspired search procedure for finding the exact or approximate solutions to optimization problems.

This paper investigates robust biologically-inspired algorithms and also draws the algorithmic profiles when these algorithms are applied to wireless mobile sensor networks. The rest of this paper is organized as follows. In Section II, we provide a brief introduction to ACO which is based upon the collective shortest-path searching behaviors in ant colonies. According to the ACO principles described in Section II, we investigate various flavors of the Ant-based routing algorithms for sensor networks in Section III. In Section IV, we introduce the GA that simulates the process of genetic selections and the GA-based routing schemes for the wireless heterogeneous networks. The concluding remarks are drawn in Section V.

II. ACO

In this section, a brief introduction to ACO is given and the problem of stagnation which commonly appears in ACO is discussed. A review of the ACO-based routing algorithm is subsequently provided.

A. ACO

The ideas of using ACO to find an optimal path can be found in [17] and [31]–[33]. Suppose that there are two ants and two routes leading to a food source; R_1 and R_2 , such that the length of R_1 is greater than the length of R_2 . Along the two routes, there are six nodes: N_e (nest), N_1, N_2, N_3, N_4 , and F_o (food source). At the beginning, both ants (A_1 and A_2) are at the starting point N_e (nest) and they have to select one of the two routes to reach the food F_o , as depicted in Fig. 1.

An example of the procedure of finding the shortest path towards the food by these ants is described as follows.

- 1) At N_e , both ants have no knowledge about the location of the food. Hence, they arbitrarily select one path from these two routes. Suppose that ant A_1 chooses the route R_1 , and ant A_2 chooses the route R_2 .
- 2) As A_1 moves along R_1 and A_2 moves along R_2 , the ants leave some amount of pheromone along their paths $F_{R_{11}}$ and $F_{R_{12}}$, respectively.
- 3) Since $R_2 < R_1$, A_2 reaches F_o before A_1 . When A_2 traverses R_2 to reach F_o , the value of $F_{R_{12}}$ will be set equal to 1, but A_1 has not reached F_o and the value of $F_{R_{11}}$ will be set to 0. To return to the nest from the food, A_2 has to choose between R_1 and R_2 . At F_o , A_2 detects that $F_{R_{12}} > F_{R_{11}}$, and therefore, has a preference for route R_2 . Suppose that A_2 chooses R_2 .
- 4) As A_2 traverses R_2 for the second time to reach N_e , $F_{R_{12}}$ becomes 2. The incremental value of $F_{R_{12}}$ confirms again that R_2 is the shortest path. When A_1 reaches F_o , $F_{R_{12}} = 2$, and $F_{R_{11}} = 1$. Hence, A_1 is more likely to select path R_2 to return to N_e .

In this example, any ant at F_o (respectively, N_e) will be able to determine the optimal path once another ant reaches F_o (respectively, N_e). If an ant is at a choice point when there is no pheromone, it makes a random decision to take either R_1 or R_2 with a probability of 0.5 for each route. However, when pheromone is present, there is a *higher probability* that the ant will choose the path with the higher concentration of pheromone. The previous example in Fig. 1 was presented by Schoonderwoerd *et al.* [32] to illustrate the pheromone trail laying and it was in turn adopted from [34]. In [34], Beckers *et al.* described the pheromone trail laying by a type of ants known as *Lasius Niger*, which dispose pheromone when traveling *both* to and from the nest [15]. However, it is noted that there are other types of ants that adopt the pheromone trail laying [35]. Furthermore, there are some other ACO approaches (e.g., AntNet [18], [36]) that used the *privileged pheromone laying* (see Section II-B), in which ants only dispose pheromones during their return trips.

B. Stagnation in Network Routing

Stagnation occurs when a network reaches its convergence (or equilibrium state); an optimal path is chosen cooperatively by all ants and this recursively increases an ant's preference for the optimal path p_o . This may lead to the following problems: 1) the congestion of p_o and 2) the dramatic reduction of the probability of selecting other paths. These two issues are undesirable for a dynamic network because of the following reasons: 1) p_o may become nonoptimal if it is congested; 2) p_o may be disconnected due to network overload or failure; or 3) other nonoptimal paths may become optimal due to the dynamical changes in the network topology. Furthermore, Bonabeau *et al.* have pointed out that the success of ants in collectively locating the shortest path is only statistical [13]. If by chance, many of the ants initially choose a nonoptimal path, other ants are more likely to select such a nonoptimal path leading to the further reinforcement of the pheromone concentration along this nonoptimal path [37]. This phenomenon is foreseeable but undesirable

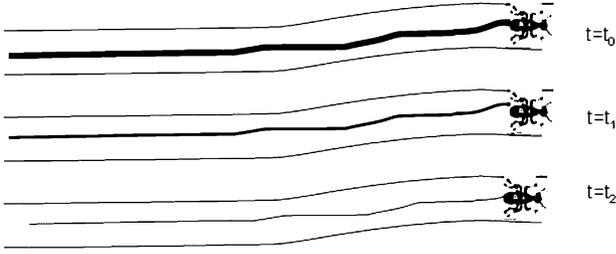


Fig. 2. Evaporation effect of ants' pheromone disposition.

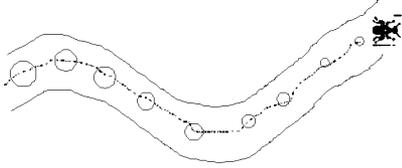


Fig. 3. Aging effect of ants' pheromone disposition.

since it is inefficient if ants always choose such a *stagnant path* that is nonoptimal.

To alleviate this stagnation problem, three main approaches are utilized: *pheromone control*, *pheromone-heuristic control*, and *privileged pheromone laying*. We will discuss these in the following.

Pheromone Control: Pheromone control provides several methods to reduce the influences from past experience and encourages the exploration of new paths or the paths that were previously deemed nonoptimal. We address some methods here.

- 1) **Evaporation Method:** to reduce the misleading effect of the past experience, an approach called evaporation in [18] is typically used in conjunction with ACO. The evaporation method prevents the pheromone concentration in the optimal paths from being too high for ants to explore other (new or better) alternatives. In each iteration of this method, the pheromone values at all vertices of the paths are discounted by a factor. An example of the evaporation is shown in Fig. 2. Suppose that at some iteration ($t = t_0$), all ants converge on a path and dispose of a very high concentration of pheromone (represented by a thick line). In the next iteration ($t = t_1$), the pheromone concentration is reduced by some factor (represented by a thinner line), and at $t = t_2$, the pheromone concentration is further reduced.

- 2) **Aging Method:** past experience can also be reduced by controlling the amount of pheromone disposed by each ant according to its age. This approach is known as *aging* [32]. In the aging mechanism, an ant disposes less and less pheromone as it moves from node to node (see Fig. 3). Aging is simply based on the fact that "old" ants are less useful in locating the optimal paths since they may have to spend a longer time to reach their destinations. Both aging and evaporation include a decaying factor of the routing preference. Hence, if a favorable path has not been chosen recently, its preference will gradually diminish. With the continuous update of the history for the pheromone disposition, both aging and evaporation increase the chance to discover new paths that were previously deemed nonoptimal.

- 3) **Limiting and Smoothing Pheromone Method:** Stuzle and Hoos mitigated stagnation by limiting the maximum allowable amount of pheromone in every path [38]. With an upper limit F_{\max} on the amount of pheromone for every link in a network, the preference of an ant for choosing optimal paths over nonoptimal ones is reduced [39]. This approach prevents the situation of generating a constantly dominant path. A variant of such an approach is called *pheromone smoothing* [39]. In the pheromone smoothing scheme, the amount of pheromone $F_{(k,l)}(t')$ evolved from $F_{(k,l)}(t)$ along a link (k,l) between node k and node l is updated as follows:

$$F_{(k,l)}(t') = F_{(k,l)}(t) + c \times [F_{\max} - F_{(k,l)}(t)] \quad (1)$$

where c is a number between 0 and 1. According to (1), as $F_{(k,l)}(t) \rightarrow F_{\max}$, a smaller amount of pheromone is reinforced along the link (k,l) . Although not identical, the pheromone smoothing method is similar to the evaporation method in some respects. While the evaporation method adopts a uniform discount rate for every path, the pheromone smoothing method leads to a relatively greater reduction in the reinforcement of pheromone concentration on an optimal path. Therefore, the pheromone smoothing method seems to be more efficient in combating the stagnation problem.

Pheromone-Heuristic Control: Another approach to mitigate the stagnation is to configure ants so that they do not solely rely on sensing pheromone for their routing. This can be accomplished by configuring the probability function $P_{k,l}$ for an ant to choose a link (k,l) using a combination of both pheromone concentration $F_{k,l}$ and heuristic function $\eta_{k,l}$. As noted in [22] and [28], an ant selects a link probabilistically using $F_{k,l}$ and $\eta_{k,l}$ as a functional composition for $P_{k,l}$. In a network routing, $\eta_{k,l}$ is a function of the costs associated with link (k,l) . The value of $\eta_{k,l}$ may be determined by the linking information such as queue length, distance, and delay. In [22] and [39], $\eta_{k,l}$ is determined by the queue length $q_{k,l}$ and $\eta_{k,l}$ as

$$\eta_{k,l} = 1 - \frac{q_{k,l}}{\sum_{i \in N_k} q_{k,i}} \quad (2)$$

where N_k denotes the set of all available interconnecting nodes. In [39], $P_{k,l}$ at time t is characterized as

$$P_{k,l}(t) = \frac{[F_{k,l}(t)]^a [\eta_{k,l}]^b}{\sum_k [F_{k,l}(t)]^a [\eta_{k,l}]^b} \quad (3)$$

where a and b specify the respective adjustable weights of $F_{k,l}$ and $\eta_{k,l}$. Hence, the routing selection of ants can be tuned according to the different values of a and b . If $a > b$, ants prefer the paths with higher pheromone concentrations, and a higher value of b increases the chance for ants to choose the paths having higher concentration values. In general, different values of a and b are selected to fit the different states of a network. A lower value of a is generally preferred when the pheromone concentration along the paths may not necessarily reflect its optimality.

Examples of such situations include the initial stage after setting up a new network (before the network stabilizes), and when there are frequent changes in the network status due to either link (or node) failure or insertion of new links (nodes). However, as a network becomes stable, a higher value of a is preferred. Furthermore, recent research in [39] has demonstrated that dynamically altering the values of a and b corresponding to the changes in the network status may improve the performance of ants' cooperative routing.

Privileged Pheromone Laying: One of the early enhancements for the ACO algorithm is to mitigate the stagnation by adopting the policy of the privileged pheromone laying [18], [40]. Experiments in [18] and [40] demonstrated that by permitting a selected subset of ants which have the privilege to dispose larger amounts of pheromone than others, the time for the ants' routing to converge to a solution reduces significantly. In this approach, the following two important questions are addressed: 1) the evaluation for the quality of the solution for ants and 2) the number of ants to be selected to dispose extra pheromone and the surplus amount of pheromone those ants are permitted to dispose. One of the simplest approaches to assess the quality of the solutions for ants is to just compare their forward-trip durations. Alternatively, employing a *fitness-landscape* (FDC) approach, Stuzle and Hoos compared the forward-trip time of each ant with the optimal forward-trip time [38].

In the FDC, the destination node records the optimal forward-trip time T_{opt} (based on the observation) and the solution of an ant is assessed by a nonlinear function specifying how close the forward-trip time of an ant is to T_{opt} . To illustrate this concept, a simple example is shown in Fig. 4. In Fig. 4(a), originating from different sources, three ants A_1 , A_2 , and A_3 arrive at the destination, each via a different path. Following the FDC approach, at the destination, the optimal forward-trip time is recorded (based on the previous observation), and all of the forward-trip times of ants A_1 , A_2 , and A_3 are compared with T_{opt} . In this example, since A_1 arrives first at the destination, its forward-trip time is closest to T_{opt} . For the case in which A_1 arrives at the destination with a smaller forward-trip time, the original value of T_{opt} will be updated accordingly. Consequently, A_1 will dispose the largest amount of pheromone on its return trip via the same path from which it came. Since A_2 arrives after A_1 , and A_3 arrives after A_2 , on their return trips via the same paths they came from, A_2 will dispose more pheromone than A_3 , but less than A_1 [shown in Fig. 4(b)].

In summary, the FDC function evaluates the *fitness* of a solution by comparing the solution of each ant with respect to the optimality. Since the solutions are compared (the fitness of each path is evaluated) before ants dispose their pheromone, Stuzle and Hoos have found that using the FDC analysis, more accurate results can be obtained [38]. In their approach, since the amount of disposed pheromone corresponds to the time delay of the trip, an ant will dispose less pheromone along a path that is longer or congested. Consequently, this reduces the chance of ants intensifying a stagnant path that is nonoptimal or congested. In the previous example, all three ants dispose pheromone in different amounts on their return trips. In other approaches, such as [41], only a subset of ants dispose pheromone, and in [38], only the best ant disposes pheromone on its return trip, which restricts the number of ants to make their return trips.

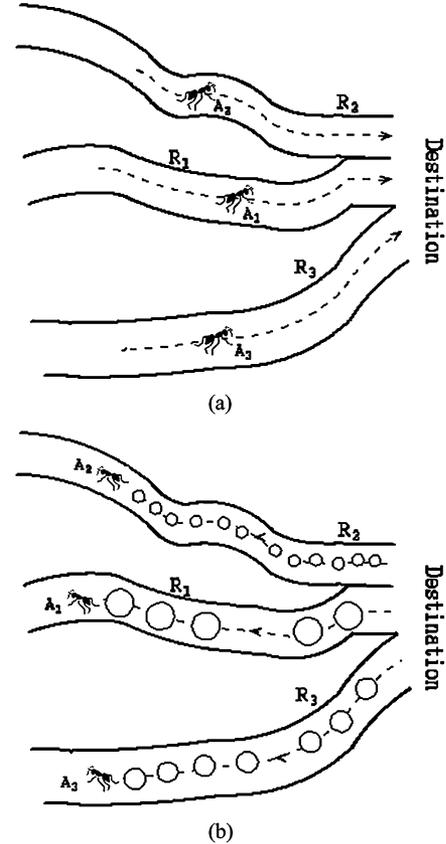


Fig. 4. (a) Three ants arrive at the same destination through different paths. (b) These ants dispose different amounts of pheromone on their return trips (denoted as the circles with different sizes).

III. ACO-BASED ROUTING ALGORITHMS

Recently, some ACO-based routing algorithms (often referred as “Ant-based” [15], [31] or “ant-like” [17]) have emerged for the employment with circuit-switch and voice-application networks [31], wired networks [18], mobile *ad hoc* networks, and sensor networks [21]. Although these different biologically-inspired routing algorithms are designed in different ways to satisfy various objectives, they share the common ACO mechanisms, such as *pheromone updating rules* and *transition rules*. Typically, the pheromone level represents the preference of the selected route, which is communicated by the ants. Different design aspects or metrics can be reflected by the pheromone updating and transition rules. In this section, we will review some important algorithms to demonstrate how ACO is used for routing in a network, and how the pheromone updating and probabilistic transition rules are formulated thereupon. We will first study the routing problem in the traditional wired network and then extend our studies to the wireless *ad hoc* networks.

A. ACO in Wired Nets

Ant-based control (ABC) is a pioneering routing algorithm designed for use with circuit-switched telephony networks [15]. In ABC, each network node preserves a *routing table* where each row corresponds to the destination nodes and each column corresponds to a neighbor. Once such a table is established, each

entry denotes the next-hop probability associated with each destination. The packets can be modeled as the ants traverse the network and update the routing tables at every node in accordance with the age of the arriving ant (the duration for the packet survival in the net). The chance of an ant's arrival at a node (the arrival rate of a packet) decreases with the age of the ant (the packet survival duration). The reciprocal of an ant's age can be deemed as the *pheromone* concentration, although there is no explicit pheromone formulation. Thus, if an ant arrives at a node, the chance of an ant's arrival is governed by the *normalized probabilistic transition rule* for the new cell entry as

$$p = \frac{(p_{\text{old}} + \Delta p)}{(1 + \Delta p)} \quad (4)$$

where p_{old} is the previous probability for an ant's arrival and $\Delta p = A/\text{age} + B$, A , and B are the design parameters. This ABC mechanism facilitates a potential solution to the dynamical routing problem and performs very well for British Telecommunications Networks [15].

AntNet in [18] solved the routing problems in wired networks, in which each node preserves the probabilistic entries in a routing table like the aforementioned ABC scheme. In an actual network operation, the next-hop node with the highest probability among all is always chosen. Each node periodically sends an exploration agent called *forward ant* to the randomly selected destinations. The forward ants record their arrival times and the node identities in a stack when every node is visited. An ant reaching its destination is immediately converted to a *backward ant* and it returns to the source node following the path in reverse. Then, each intermediate node updates its routing tables according to the information extracted from the backward ants. For example, the probability of the route with shorter round-trip time will be increased due to the frequent travels of the ants.

Algorithms that were inspired from real ants' behavior in finding the shortest paths have recently been successfully applied to several discrete optimization problems [34], [39]. For all ACO-inspired algorithms presented before 1998, a set of artificial ants collectively solve the problems through a cooperative method. This method is mediated by the indirect communication of the information the ants concurrently collect while the corresponding solutions are based on stochastic policies. Similarly, in AntNet, the algorithm proposed by [18], a set of distributed agents (ants) collectively solve the adaptive routing problem concurrently. Agents update the routing tables and the local models of the network status via indirect and noncoordinated communication of the information they collect during the exploration of the network. To ensure a meaningful validation of their algorithm performance, a realistic and complete simulation environment in terms of networking characteristics, communication protocols, and traffic patterns are established in [18]. They focus on the Internet Protocol (IP) datagram networks with an irregular topology and consider three real and artificial topologies with an increasing number of nodes and several paradigmatic temporal and spatial traffic distributions [18]. AntNet manifests the best performance and the most stable behavior for realistic situations. In many experiments, AntNet almost always outperforms other network systems.

B. ACO in Global Positioning Systems (GPSs)

In [17], a novel routing algorithm called GPS/Ant-Like Routing Algorithm (GPSAL) based on GPS and mobile software agents, is introduced. The GPSAL imitates the ants' behavior for the routing in a mobile *ad hoc* network (MANET). The network system comprises MANET with mobile hosts that can communicate with each other using wireless links. The GPSAL algorithm in [17] has been compared to the location-aided routing (LAR) algorithm for MANET. Simulation results show that GPSAL induces less overhead than LAR.

The idea of the GPSAL algorithm is described as follows. Whenever a mobile node wants to join MANET, it senses the medium to find out a neighbor node, say G . Once a neighbor node G is identified, the mobile host sends a request packet to G to ask for its routing table which will be sent back to the host. From this instant, the new mobile host can start routing and send packets in MANET. The routing protocol is based on the physical location of a destination host H stored in the routing table. If there is an entry in the routing table for the host H , the best possible route is selected using a shortest path algorithm. The route, composed of a list of nodes and the corresponding timestamps, is attached to the packet which is sent to the first host in the list. If host H is not found in the routing table, the mobile node sends a message to the nearest static node, if available, for finding the destination node. Otherwise, the data packet is not delivered. Therefore, each host, upon receiving a packet, compares the routing information present in the header with that in its routing table. The entries that have older information than that in the received packet are updated. This is performed by comparing the timestamp field in the received packet header and that in the routing table. Furthermore, each intermediate node can change the route to a destination node when there is a better route. How to update the routing table is an important aspect for MANETs. It is obvious that better routes can be determined whenever a host has new dynamic information about the network configuration. Routing information can be obtained both locally and globally. Local information is obtained from a neighbor node that periodically broadcasts to update the information of the network configuration. Global information can be disseminated more rapidly using the mobile software agents modeled as ants in the following.

The route discovery can be accelerated using mobile software agents modeled as the ants which are responsible for collecting and spreading more up-to-date location information of the mobile hosts. When a host receives an ant's message, it compares the routing table present in the ant's packet with its routing table and then updates the entries that have older information therein. When this ant leaves a node, it carries the newest routing table from the underlying nodes it has already visited plus the current one. This crucial dynamic process can lead to a good routing performance.

C. Swarm Intelligence Using Stigmergy in Ad Hoc Networks

A new approach for an on-demand *ad hoc* routing algorithm (ARA), which is based on *swarm intelligence*, is presented in [21]. ACO algorithms are a subset of swarm intelligence and

rely on the ability of simple ants to solve complex problems cooperatively. The important observation is, that the ants do not need any direct communications for the solution process; instead, they communicate with each other by *stigmergy*. The notion of stigmergy means the indirect communication of the concerned individuals through changing their environment. Several algorithms which are based on the ACO incentives were introduced in recent years to solve different problems. For utilizing the characteristics of stigmergy, an ACO-based routing scheme ARA for MANET was introduced in [21]. Its route discovery mechanisms are similar to dynamic source routing (DSR). In [21], the route discovery is performed by flooding forward ants to the destination as well as establishing the reverse links to the source. The routes' maintenance in ARA does not need any extra particular messages in transmission. Once the pheromone loci have been established for the source and destination nodes, the data packets are used to maintain the path. In ARA, the pheromone updating rule resembles the rule formulated in the following equation for ACO:

$$\varphi_{ij}(t) = (1 - \rho)\varphi_{ij}(t) + \sum_{k=1}^m \Delta\varphi_{ij}^k(t) \quad (5)$$

where $\varphi_{ij}(t)$ is the pheromone trail from node i to j , ρ is the decay factor and $\Delta\varphi_{ij}^k(t)$ is the quantity of pheromone laid on edge (i, j) by ant k . Consequently, the transition probabilities for a node to choose the next-hop is expressed as

$$p_{ij}^k(t) = \frac{[\varphi_{ij}(t)]^\alpha}{\sum_l [\varphi_{il}(t)]^\alpha}. \quad (6)$$

In [18], a routing scheme for MANET has been proposed which combines the on-demand routing capability of the *ad hoc* on-demand distance vector (AODV) routing protocol with a distributed topology discovery mechanism using ant-like mobile agents. The proposed hybrid protocol reduces the route discovery time and the end-to-end delay by providing high connectivity without much sacrifice of network capacity. Since the proactive routing protocols in the MANETs, such as destination sequenced distance vector (DSDV), require the knowledge of the entire network topology, they are not very effective in highly dynamic networks, the updated topology information needs to be frequently propagated throughout the dynamic network. These frequent broadcasting operations limit the achievable network capacity for actual data communication. The on-demand routing schemes like AODV and DSR require the actual data transmission to be delayed until the route is selected. Due to this long delay, a purely reactive routing protocol may not be proper for real-time data communications. Therefore, the Ant-AODV hybrid routing protocol has been proposed.

The integration of Ant-based routing and AODV routing protocols will overcome some of their inherent disadvantages. The hybrid scheme enhances the node connectivity and decreases the end-to-end delay as well as the route discovery latency. The route establishment in the conventional Ant-based techniques depends on the ants' visiting the nodes. If a node attempts to send data packets to a destination for which it does not have enough routes, it will have to relay the data packets in its sending buffer long enough until an ant arrives and presents a route to

that destination. In addition to this drawback, there is no local connectivity maintenance as in AODV for the implementation of the Ant-based routing algorithms so far. Hence, it is possible for a source to keep sending packets even though the failure of the link occurs but is not recognized. This leads to a large number of unsuccessful transmissions due to the packets continually getting lost.

On the other hand, the AODV scheme takes too much time for the connection establishment due to the processing delay for the route discovery. The deployment of ants in AODV increases the node connectivity (the number of destinations for which a node has unexpired routes) and also reduces the amount of route discovery. Even if a node launches an RREQ for a destination that does not have enough viable routes, the probability of its receiving the replies quickly (as compared to AODV) from the neighboring nodes is high due to the increased connectivity of all the nodes, which results in a reduced route discovery latency. As ant agents update the routes continuously, a source node can switch from a longer route to a newer and shorter route identified by the ants. This leads to a considerable decrease in the average end-to-end delay as compared to both AODV and Ant-based routing individually. Ant-AODV protocols utilize the route error messages (RERR) to inform the upstream nodes of any local link failure similar to AODV. The routing table in Ant-AODV is common to both Ant-based routing protocol and AODV. Frequent HELLO broadcasts are also undertaken to maintain a neighbor table. This table is used to randomly select the next-hop (avoiding the previously visited node) from the list of neighbors by the ant agents.

D. Adaptive Stigmergy-Based Routing for Wireless Networks

A biologically inspired algorithm is presented to route the messages in mobile wireless *ad hoc* networks. An adaptive algorithm, dubbed *Termite*, using stigmergy has been proposed to reduce the amount of control traffic needed to maintain a high data throughput [38]. The disposed stigmergy will have an influence on the adaptive routing table. The termite environment requires the contents of all routing tables. The movement of packets is influenced at each node and the communicating nodes observe this influence and update their own tables accordingly. The routing robustness is achieved through the use of multiple paths; each packet is routed randomly and independently.

Termite is a routing protocol for wireless mobile *ad hoc* networks based on the principles of swarm intelligence [42]. This framework is used to define the rules for each packet to follow, which result in emergent routing behaviors. Other additional advantages include reduced control traffic as well as quick route discovery and repair. As packets are dispatched from a source to a destination, each packet follows a preference (bias) towards its destination while the packet will follow the updated preference (not necessarily identical to the forward trip) back to its source. This bias is known as pheromone. Pheromone is laid on the communications links between nodes along the paths. Packets are attracted towards strong pheromone concentration but the next hop is always randomly decided if there is no pheromone. Following a destination pheromone trail and disposing the source pheromone along the same trail increases the likelihood of the packets to retrieve the reverse

path back to the source. This is positive feedback. In order to prevent the old routing decision from influencing the network memory, an exponential pheromone decay is introduced as negative feedback. Pheromone increases linearly per packet, but decreases exponentially over time. Like real pheromone, the artificial pheromone concentration decreases with time to avoid a fast convergence of pheromone on the network edges. In the termite routing, an exponential decay equation is adopted as

$$\varphi_{ij}(t) = e^{-t} \varphi_{ij}(t) + \Delta \varphi_{ij}(t) \quad (7)$$

where t is the elapsed time, $\varphi_{ij}(t)$ is the pheromone in the network memory, and $\Delta \varphi_{ij}(t)$ is the current update.

E. Distributed ACO Routing Algorithm (ADRA) in Ad Hoc Networks

An Ant-based distributed route algorithm for *ad hoc* networks (ADRA) has been proposed in [29]. The ants travel across the network between randomly picked pairs of nodes. As they move, they dispose of the simulated pheromones as a function of their traveling distance from their source node, the quality of the link, the congestion encountered on their journey, the current pheromones the nodes possess, and the nodes' moving speeds. The node changes the pheromones by itself according to the quality and age of the link by evaporating the pheromones. The ants select their path at each intermediate node according to the distribution of the simulated pheromones. In order to accelerate the convergence rate of the congestion and shortcut problem, the proposed method in [29] assigns the parameters with different weight values to update the probability routing table. The performance of this algorithm is measured by the packet loss ratio, control overhead, and end-to-end packet delays. The ADRA system is shown to result in fewer call failures than other methods and exhibit many attractive features for distributed network control.

There are several advantages of the ADRA algorithm: 1) the algorithm can improve the convergence rate of the Ant-based routing in an *ad hoc* network; 2) the control overhead introduced by a large number of ants can be reduced; 3) the congestion problem and the shortcut problem can be alleviated quite well; 4) the network load balance can be achieved; and 5) the end-to-end delay of the packet transmission can be mitigated. Essentially, endowing several separate quality-of-service (QoS) parameters with different weights to update the pheromone strengths and the probability routing tables, ADRA efficiently implements the distributed scheme for the optimal route selections and reselections via intermediate nodes and thus balances the network traffic [26], [43]. Through the control of the pheromone strength in accordance with the QoS parameters, ADRA can properly distribute the traffic prior to the probable congestion and accelerate the convergence of the solution to the congestion problem with the help of congestion repression ants, i.e., *anti-ant*. Similarly, the shortcut problem can be solved by introducing the shortcut reinforce ant, i.e., *enforce-ant*. When an intermediate node's load exceeds its predefined congestion threshold, it will send a congestion-control *anti-ant* to its upstream neighbor nodes to modify their probability routing tables. Upon receiving an *enforce-ant* or an *anti-ant*, the node

updates the routing table accordingly to reinforce the good route and avoid the congested one.

IV. GENETIC ROUTING ALGORITHM

In this section, we will discuss the genetic algorithms which are used for GA-based routing in wireless sensor networks [44]. In [45], a mobile agent-based paradigm for data fusion in the distributed sensor networks is presented. By utilizing a simplified analytical model for a distributed sensor network, a route computation problem for the mobile agent is formulated in terms of the maximization of the received signal strength, normalized by the path loss and the energy consumption. Because the implementation of the proposed routing algorithm is an NP-hard problem, it becomes impossible to develop a polynomial-time algorithm to compute an optimal route. Hence, two-level GAs were proposed to solve this problem by employing two-level genetic encoding and genetic operators. Simulation results have been presented for the comparison between the GA-based routing and the existing LCF and GCF heuristics. Various advantages of the GA algorithm, such as computational complexity, network structure, and route quality, are discussed in [45].

Genetic algorithms are categorized as global search heuristics. Genetic algorithms are a particular class of evolutionary algorithms which rely on techniques inspired by evolutionary biology, such as inheritance, mutation, selection, and recombination. Genetic algorithms are implemented using computer simulations in which a population of abstract representations (also called chromosomes, the genotype or the genome) of candidate solutions (called individuals, creatures, or phenotypes) are transformed into an optimization problem. Basically, the solutions are coded and quantized as binary strings consisting of 0's and 1's, but other codebooks are also allowable. The evolution usually starts from a population of randomly generated individuals. In each subsequent generation (iteration), the fitness of every individual in the population is evaluated and multiple individuals are stochastically selected from the current population according to their fitness and modified to form a new population by possible combinations and mutations. The new population is then used in the next iteration of the algorithm. Nowadays, genetic algorithms are widely adopted in computer science, engineering, economics, chemistry, physics, mathematics, and other fields.

Ad hoc sensor networks, comprising a large number of randomly deployed wireless sensors, have recently attracted interest. These networks require a self-organized configuration after deployment and the *ad hoc* heuristic methods for such a configuration have been proposed with regard to many aspects of the networking performance [46]. However, systematic approaches for a self-organized configuration remain unclear. In [47], a first attempt to take a systematic approach using GAs was presented and it focused on the problem of heterogeneous networks to optimize global functional properties through local adaptive rules. Almost all work on the *ad hoc* sensor networks has so far involved homogeneous networks where all nodes transmit messages at the same power level so as to create a symmetric connectivity. It is possible to construct heterogeneous networks by allowing the nodes to transmit at different

power levels. Such heterogeneous networks lead to improvements in network lifetime, power efficiency, and routing. However, heterogeneous networks are difficult to build, mainly because the optimal power level for each node depends on the node location and spatial context, which are not known before any deployment. A few heuristic schemes focused on improving power consumption have been proposed in the literature, but the issue has not been investigated sufficiently within a generalized framework. In [47], a GA is used to generate a set of heterogeneous sensor networks that are characterized by low short paths and minimal congestion. This experiment shows that the adapted networks using this heuristic produce significant improvement over the homogeneous networks. More importantly, the results validate that the GA approach can be used in other self-organizing systems.

V. CONCLUSION

The goal of this paper is to provide a comprehensive overview of biologically-inspired algorithms governing important routing problems in wireless mobile sensor networks. Biologically-inspired collective intelligence has been studied and some biologically-inspired methodologies are investigated, including ACO approaches and GAs. The implementations of these methods for routing in various dynamical and heterogeneous networks are investigated. These biologically-inspired routing mechanisms can have various advantages over the conventional centralized schemes in congestion avoidance, end-to-end delay mitigation decreases, processing delay, and computational complexity reduction.

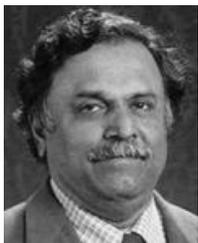
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