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A New Routing Algorithm for Vehicular Ad-hoc Networks based on Glowworm Swarm Optimization Algorithm

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Abstract
Vehicular Ad hoc NETworks (VANETs) are a particular type of Mobile Ad hoc NETworks (MANETs) in which the vehicles are considered as nodes. Due to the rapid topology change and frequent disconnection in these networks, it is difficult to design an efficient routing protocol for routing data among vehicles. In this work, a new routing protocol is provided based on the glowworm swarm optimization algorithm. By using the glowworm algorithm, the proposed protocol detects the optimal route between three-way and intersections. Then the packets are delivered based on the selected routes. The proposed algorithm assigns a value to each route from a source to the destination using the glowworm swarm optimization algorithm, which is a distributed heuristic algorithm. Then a route with a higher value is selected to send messages from the source to the destination. The simulation results show that the proposed algorithm has a better performance than the similar algorithms.

Keywords: *Vehicular Ad Hoc Networks, Routing, Glowworm Swarm Optimization, Urban Environments, Data Delivery Delay.*

1. Introduction
Intelligent Transportation Systems (ITSs) present a technology that can be applied to vehicles as well as infrastructure to transfer information between them to improve minimizing traffic congestion, safety, and productivity. ITSs are advanced applications used to provide the services related to transport and traffic management, and allow the users to be better informed and make a safer, more coordinated, and smarter use of transport networks. Vehicular Ad hoc NETworks (VANETs) are a key component of ITSs [1,2,3].
VANETs are a particular type of Mobile Ad hoc NETworks (MANETs) in which the vehicles are considered as nodes. Unlike MANETs, the vehicles move on the predetermined routes (roads), and their velocity depends on the road traffic and restrictions [4]. The main challenge in VANETs is to maintain the communication between vehicles to send data from a source to a destination node. This data transmission is performed as a wireless and multi-hop mode. Therefore, the design of an efficient data transmission protocol in VANETs is one of the most important issues [5-7] on which many studies have been conducted and several methods have been proposed to solve it. Despite the different approaches proposed so far, a comprehensive approach to address this issue has not been provided yet [8-11]. Complications arise due to the specific features of VANETs. Some of the important features of VANETs are as follow: the frequent and high-speed movement of vehicles in these networks and the high dynamism of the network topology, frequent disconnection, the environment in which the network works (in environments such as city centers where there is a higher density and forecasting the vehicle movement is much more difficult, and in the areas where there are obstacles causing more delays and problems in the vehicular communication) [6,7]. These features make it impossible to use traditional ad hoc networks' routing algorithms in VANETs. An efficient routing algorithm means that it can choose an optimal route to transmit a

message from a source to a destination [12]. Searching for feasible routes subject to multiple Quality of Service (QoS) constraints is, in general, an NP-hard problem [15]. In the rest of this paper, we use the QoS routing to refer to this problem.

Considerable works have been carried out to address QoS routing in VANETs [5,6,9]. Among them, heuristic routing algorithms have been more successful [12]. In these networks, it is not possible to use each one of the heuristic algorithms due to the specific characteristics of these networks such as the lack of an infrastructure or a global server. The proper heuristic algorithms for these networks are distribute heuristic algorithms such as ant colony algorithm. In designing a routing algorithm for VANETs using distributed heuristic algorithms, there is no need to have a complete view of all nodes in the network to generate a routing among them. Therefore, it is possible to design a distributed routing algorithm. Recently, a distributed heuristic algorithm called Glowworm Swarm Optimization (GSO) has been proposed, which has a better performance than the other distributed heuristic algorithms such as ant colony algorithm [10]. Therefore, a proper use of GSO to address QoS routing in VANETs can lead to a better routing algorithm for these networks. On the other hand, the distributed heuristic algorithms used to address QoS routing in VANETs [5,6,9,12] generate an approximate solution for the problem, and generating a better solution for this problem is still an open problem.

In this work, a routing protocol is provided to transmit information in VANETs.

The proposed protocol uses the Glowworm Swarm Optimization (GSO) algorithm [13]. Using this algorithm, the proposed protocol detects an optimal route among three-ways and intersections. Accordingly, the packets reach their destination through an optimal or near-optimal route. The simulation results show that the proposed algorithm has a better performance than the similar algorithms.

The rest of this paper is organized as what follows. In the next section, the related works are described. Section 3 presents an overview of the GSO algorithm. Section 4 describes the network model. Our proposed algorithm is presented in detail in Section 5. To evaluate the performance of the proposed algorithm, the simulation setup and the results obtained are presented in Section 6. Finally, Section 7 concludes the paper.

2. Related works

Searching for feasible routes subject to multiple QoS constraints is, in general, an NP-hard problem [15]. Many works have been proposed so far to address this problem. Generally, there are two distinct approaches adopted to solve the routing problem in VANETs, exact QoS routing algorithms, and heuristic and approximation routing algorithms. Distributed heuristic algorithms provide a better network performance. In what follows, a number of works with a better performance than the similar algorithm are reviewed.

In [15], the Situation-Aware Multi-constrained QoS (SAMQ) routing algorithm has been proposed for VANETs to find an optimal path between two nodes to improve a set of QoS parameters. This problem is, in general, an optimization and NP-hard problem. To solve this problem, the heuristic and meta-heuristic algorithms are used. In [15], the ant colony optimization algorithm has been used, and a good approximate answer has been obtained for this problem. The algorithm presented in [15] uses the vehicles' position to obtain enough data to solve the problem.

In [16], a routing algorithm has been proposed by GPS in a given urban area. This algorithm uses the topology characteristics and a sparse matrix to find a multi-hop route between vehicles. In fact, based on the information from the network, a sparse matrix is formed by which the route can be found. To use this method, the data should be collected thoroughly and processed in a place such as a server, and a route is determined. There are problems such as server update in the use of a central server.

In [17], the Intelligent Adjustment Forwarding (IAF) algorithm has been proposed. IAF is an application layer forwarding algorithm incorporation TCP and VANET routing at its lower layers. In IAF, a segment-to-segment transmission strategy is used to optimize the data delivery performance. The proposed scheme achieves an effective trade-off between the efficiency and the reliability of the data transmissions. Moreover, the scheme adjusts the segment size adaptively in accordance with the current network conditions (as indicated by the link state), thereby maximizing the delivery ratio while simultaneously minimizing the delivery delay.

In [18], Lightweight Intersection-based Traffic-Aware Routing (LITAR) has been proposed for V2V communication in urban vehicular networks. LITAR introduces two new algorithms to reduce the network overhead generated by the traffic status measurement process while preserving the accuracy of measurement. Moreover, LITAR makes routing decisions based on vehicular directional density, Road Network Connectivity (RNC), and distance towards the destination.

In [19], a new opportunistic-based routing algorithm (OSTD) has been proposed for urban scenarios. In this method, the vehicles consider various parameters to select the message transfer path. These parameters include distance, distribution of vehicles in the area, and vehicles' density. In fact, in the OSTD algorithm, when a vehicle reaches a three-way or intersection, calculates these three parameters for each route. To choose the best path to transmit the message to the destination, OSTD allocates a value to each path according to the three parameters, and a path with the best value is selected as the appropriate path for message transmission.

In [20], a Hybrid Bee swarm Routing (HyBR) protocol has been proposed for VANETs. HyBR is based on the continuous learning paradigm in order to take into account the dynamic environmental changes in real-time. HyBR combines the features of topology routing with those of geographic routing, and is a unicast and a multi-path routing protocol.

In [21], a routing protocol based on Ant Colony Optimization (ACO) has been proposed for VANETs. In this work, the authors have regarded the dynamic route selection with the best QoS as an optimization problem, and make use of the ACO algorithm to solve this NP-hard problem. In this method, several ants are sent to explore the available routing paths between intersections. In the data packets forwarding, this protocol dynamically chooses the best next intersection for data packets, and when forwarded between two adjacent intersections, the data packets make use of a greedy mechanism.

All the mentioned methods to address the QoS routing problem in VANETs are approximate methods, meaning that these methods find a near optimal solution for the problem and do not find the exact solution. Each one of these methods tries to find a better solution (a more near-optimal route) for the problem.

Therefore, finding a better solution to the problem is still an open problem. In this work, we used a new distributed heuristic algorithm (GSO) to solve the QoS routing problem in VANETs. The GSO algorithm has less computational operations than the other algorithms such as ant colony, and thus it can be run faster. In fact, this method can be run for more times, and we will have an available route in VANETs.

3. Overview of GSO

The GSO algorithm was first introduced in [13]. In the GSO algorithm, the physical entities (agents) are considered, which are randomly distributed in the workspace. The agents in the GSO algorithm carry a luminescence quantity called luciferin along with them. The agents are thought of as glowworms that emit a light whose intensity is proportional to the associated luciferin, and have a variable decision range. Each glowworm is attracted by the brighter glow of other neighboring glowworms. A glowworm identifies another glowworm as a neighbor when it is located within its current local-decision domain. The agents in the glowworm algorithm are associated with the information available in the local-decision range to make their decisions. The resulting algorithm is highly decentralized. Three main assumptions are considered in this algorithm:

1. All worms are from one gender.
2. The attractiveness of each worm is proportional to its glow.
3. The glow of each worm characterizes the fitness function of the problem.

The GSO algorithm starts by placing n random member population of glowworms in the problem's search space. First, the worms have the same amount of glow (luciferin) as much as I. Each iteration includes one phase of luciferin update and one phase of updating the worms' location.

3.1. Luciferin update

The luciferin amount of each worm per iteration is determined according to the fitness of the status of the worm. It means that based on the fitness value and proportional to it, an amount of luciferin is added to the previous value per iteration. In order to model the gradual decline over time, an amount of the current luciferin with a factor (less than one) is reduced from it, and thus:

$$l_i(t+1) = (1-\rho)l_i(t) + \gamma J(x_i(t+1)) \tag{1}$$

where, $J(x_i(t+1))$ is the value of the fitness function of the worm i in iteration t of the algorithm, and ρ and γ are constant values.

3.2. Location update

For all glowworms i $(1 \le i \le n)$, the possibility of moving towards the brighter neighbor is defined as follows:

$$p_{ij}(t) = \frac{l_j(t) - l_i(t)}{\sum_{k \in N_i(t)} l_k(t) - l_i(t)} \tag{2}$$

where, $N_i(t)$ is the set of glowworms neighboring the worm i at time t. The discrete-time model of the glowworm movements can be stated as:

$$x_i(t+1) = x_i(t) + s\left(\frac{x_j(t) - x_i(t)}{\left\|x_j(t) - x_i(t)\right\|}\right) \quad (3)$$

where, $x_i(t)$ is m dimension vector of the glowworm location i at time t, $\|.\|$ is the Euclidean norm operator, and s is the step-size.

4. Network model

Before description of the proposed algorithm, some assumptions are considered in this article, as follow:

1. The urban environment is considered.
2. Every vehicle in the network is equipped with a GPS device and a digital map. Therefore, the vehicles are aware of their position and road topology at any moment.
3. Vehicles broadcast the beacon message periodically. This message contains a number of fields such as ID, position, speed, and movement direction of the vehicle. Therefore, each vehicle can find its neighbors.
4. No fixed stations are used in the environment.
5. All connections are wireless and within the urban area.

5. Proposed algorithm

The proposed algorithm finds an optimal route from a source to a destination and then sends the message through the discovered route. To discover the optimal route, it uses the GSO algorithm. Each source node sends several control messages, which are considered as the population of glowworms. Each node, on receiving a glowworm, runs two phases of the algorithm, i.e. updating the amount of luciferin and location. When the amount of luciferin of a message is updated, it will be compared with the previous amount of luciferin in the vehicular, and if it is smaller than the previous value, the previous amount is replaced with a new one. In other words, when the glowworms are sent from a source to the destination, they calculate their amount of luciferin along the path and store their luciferin in the intermediate vehicles. Therefore, after disseminating the routing control messages to the destination, the optimal path is determined using stored luciferins in the vehicles. Then the message passes through the path with the highest luciferin. In the following section, we describe the proposed algorithm in details and in a general form, and also we consider a scenario as an example by which we show how the algorithm works.

In figure 1, we assume that source S wants to send a message to the destination D. There can be different routes to send the packets from the source S to the destination D. In this figure, between the two presented routes, the first one passes the intersection A1 directly to the intersection A3. In the second one, the message reaches its destination after passing through the intersections A1, A2, A4, and A3, respectively. Thus the first route based on the intersections is S→A1→A3→D and the second one is S→A1→A2→A4→A3→D. The first route S→A1→A3→D is a shorter route (the distance considered here is the Euclidean distance), and if the message passes this route, the delay of the proposed algorithm is reduced. However, in the proposed algorithm, in addition to the short route parameter, the vehicular density is another parameter to be considered.

The purpose is to use the GSO algorithm and find the optimal path based on the distance and vehicular density so that the source node could send its data message to the destination through the optimal path.

In the proposed algorithm, similar to the AODV algorithm [14], the source S finds a route to the destination first and then sends its message through the discovered route. To discover the optimal route by the glowworm algorithm, it is assumed that the source S sends several control messages to the destination; these control messages are considered as glowworms that in each transmission from one vehicle to another vehicle, two phases of the algorithm are implemented, i.e. the amount of luciferin and location will be updated. In fact, iteration occurs per transfer, and the amount of luciferin is stored in the vehicle. When the amount of luciferin of a message is updated, it is compared with the previous amount of luciferin, and if it is smaller than the previous value, the previous amount is replaced with the new one.

When the glowworms are sent from the source S to the destination D, they calculate their amount of luciferin along the path and store them in the vehicles passing through them. Therefore, after disseminating the routing control messages (glowworms) to the destination, the optimal path is clear and the message passes through the path with the highest luciferin. Figure 2 presents a view of the network in which the glowworms are transmitted to the destination and their luciferin is calculated and stored in the intermediate vehicle.

In this figure, the path in which the vehicles are highlighted is the optimal path; it means that it is a path that has a higher luciferin.

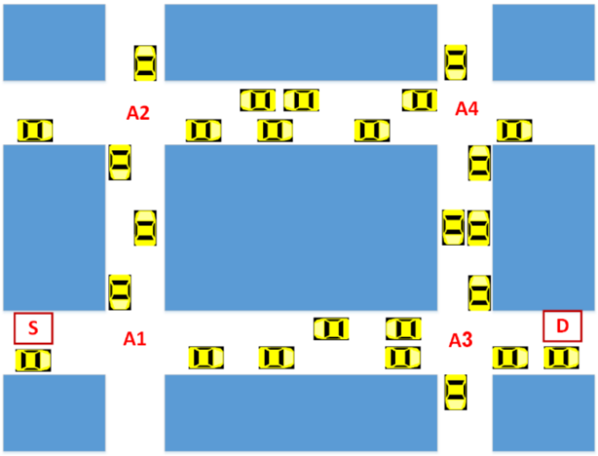

Figure 1. One example of network topology.

In figure 2 when the source S sends its message to the destination, it selects the node with the highest amount of luciferin (brighter) as the next-hop for the data message among its neighbor and sends the data message to that neighbor. Thus the highlighted route will be selected as the message transmission route. For each vehicle to have the luciferin value of its neighbors, this value is stored in the beacon message and it is sent to the nodes along this message route and stored on the table of the list of neighbors for each vehicle.

Suppose that n glowworms (control messages) are generated and transmitted by the source node. For each glowworm such as the worm i $(1 \le i \le n)$, its position vector $x_i(t)$ in the iteration t is presented as the pair $x_i(t) = (D(t), \rho(t))$, where $D(t)$ is the Euclidean distance between the source S and vehicle t, and $p(t)$ is the vehicular density between the vehicles at source S and vehicle t. The value for $p(t)$ is calculated as follows:

$$\rho(t) = \frac{N_t}{D(t)} \qquad (4)$$

where, N_t is the number of vehicles between the source S and vehicle t.

When a glowworm reaches a vehicle, it performs the following tasks, respectively:

1. It calculates the value of its position vector (it calculates the values for $D(t)$ and $p(t)$).
2. After calculation of the position vector, the glowworm updates its value of luciferin according to Equation (1). It compares the new value of luciferin with the old luciferin value calculated in the vehicle. If this value is higher than the old value stored in the vehicle, the old value is replaced by the new one.

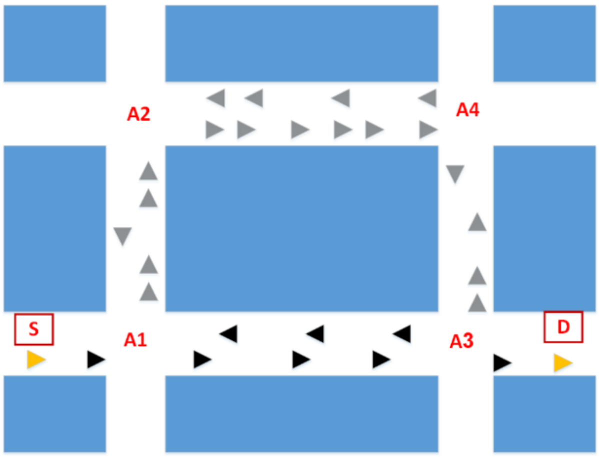

Figure 2. The path in which the vehicles are highlighted is the optimal route. In fact, the amount of calculated glowworm luciferin is higher on this route.

```
1. Create n glowworms.
2. Initialize luciferin value for each glowworm with I.
3. Send the glowworms toward D.
4. For each glowworm_i (1 ≤ i ≤ n) when reach a vehicle
5.      Compute D_i(t) and p_i(t).
6.      Update luciferin using Equation (1).
7.      Select next-hop according to the probability  Equation (2).
8.      Send glowworm_i to the next-hop.
9. End For
10. Node S sends data to neighbour with maximum luciferin
11. If (receiving node is D) then
12.      Save data message
13.      Exit.
14. Else
15.      Send data to a neighbour with maximum luciferin.
16.      Go to 11.
```

Figure 3. Pseudo-code of proposed algorithm.

3. Each glowworm, according to the probability value, chooses a neighbor of the current vehicles with a higher luciferin as its next travel destination. This probability value is calculated according to Equation (2).

5.1. Pseudo-code

Suppose that the vehicle S wants to send a message to the destination D. The pseudo-code made between the source S and the destination D based on the proposed algorithm is shown in figure 3.

In the proposed algorithm, each glowworm contains several fields. Some of the important fields are listed as what follows:

1- Source : IP of the source node.
2- (x_s, y_s) : Position of the source node.
3- x : Position of the glowworm.

4- l_i : Luciferin value.
5- N : Vehicular density.
6- Destination : IP of the destination node.

6. Performance evaluation

In this section, the proposed algorithm is evaluated by simulation. The proposed algorithm uses the GSO algorithm for routing in VANETs, and thus it is called GSO. The proposed algorithm is simulated by OMNeT++ and SUMO (Simulation of Urban Mobility) is used to generate traffic [22].

6.1. Simulation scenario

Simulation is performed in a real area with dimension 1600 m × 1400 m. The average speed of vehicles is 40-60 km/h. Ten vehicles act as the source node and randomly transmit the data message to the destination nodes periodically. Table 1 presents the list of simulation parameters.
The values for parameters ρ and γ in the glowworm swarm algorithm are 0.4 and 0.6, respectively. It has been shown in [13] that these values are the best values for these parameters. The simulation area is presented in figure 4.

6.2. Evaluation

To evaluate the performance of the GSO algorithm, this algorithm is compared with OSTD [19] and SAMQ [15]. The simulation results of all of the protocols are conducted with the same parameter values, which are given in table 1. The following performance metrics are considered in the simulations:

- **Packet delivery delay:** The time required to deliver a packet to the destination.
- **Average packet delivery ratio:** The average ratio of the number of successfully received data packets to the number of data packets sent.
- **Lost packet ratio:** The ratio of the number of lost data packets to the total number of packets.

In the simulation, it is assumed that 10 vehicles send their data to a series of random destinations periodically. The number of vehicles is considered variable between 100 and 300.
Figure 5 presents the diagrams related to the GSO, OSTD, and SAMQ algorithms to compare the delay in the message delivery.
As shown in figure 5, the delay in GSO is less than other algorithms because in GSO a node before delivering its packets finds an optimal path between source and destination using the GSO algorithm and then the data packets are delivered on this optimal route to the destination. Sending the data packets on the optimal route will reduce delays. Sending a data message on the found route is very simple and clear; each node examines its neighbours to choose the neighbour with the most amount of luciferin as its next hop and sends the message to it until the message reaches its destination. All the three methods are approximation methods, and they can find a near-optimal solution to the problem. However, as it has been shown in [14], the GSO algorithm has a better performance than ant colony. Therefore, the optimal route that is found by GSO is better than SAMQ. OSTD does not use a powerful method like heuristic methods, and it only considers three parameters to select the message transfer path. Therefore, the selected route in GSO and SAMQ is better than OSTD.
Figure 6 presents the average packet delivery ratio for the three algorithms. In the GSO algorithm, first n control packets are transferred as worms to explore the path between the source and destination, and the optimal route (specified based on Euclidean distance parameters from the source and the vehicular density) is marked. Then the nodes transfer their data packets on the brighter routes (optimal routes) to the destination; this method has a better packet delivery ratio than the other algorithms because the data packets are delivered on the optimal route to their destination.

Table 1. Simulation parameters.

Parameter	Value
Region size	1600 m × 1400 m
Number of vehicular	100, 150, 200, 250, 300
Velocity	40-60 km/h
Simulation time	600 s
Vehicle's beacon interval	1 s
Number of lanes	1 lane per direction
Communication range	300 m
Packet size	512 bytes

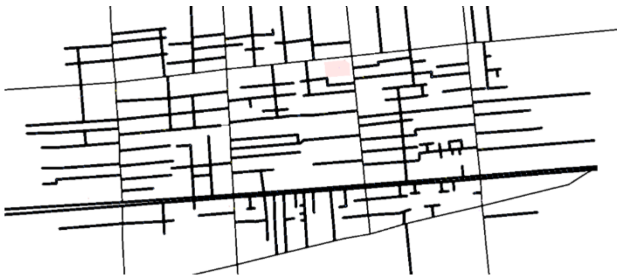

Figure 4. Simulation area.

Figure 6 presents the average packet delivery ratio for the three algorithms. In the GSO algorithm, first n control packets are transferred as worms to explore the path between the source and destination, and the optimal route (specified based on Euclidean distance parameters from the source

and the vehicular density) is marked. Then the nodes transfer their data packets on the brighter routes (optimal routes) to the destination; this method has a better packet delivery ratio than the other algorithms because the data packets are delivered on the optimal route to their destination.

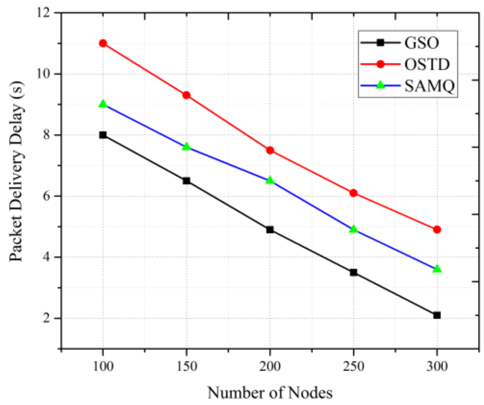

Figure 5. The delay in message delivery.

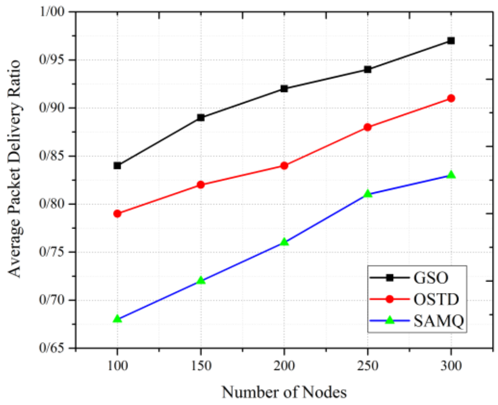

Figure 6. Average packet delivery ratio.

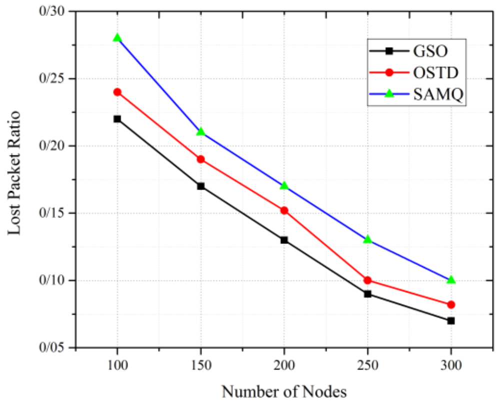

Figure 7. Lost packets ratio.

The lost packet is another important parameter evaluated in this simulation. Figure 7 compares the rate of the lost packets among the algorithms. The rate of the lost packets is calculated based on counting the total number of data packets generated by the nodes and the ones that have not been delivered. Finally, the number of undelivered data packets is divided by the number of data packets generated in all nodes.

SAMQ has the worst performance in the average packet delivery ratio and the lost packets because for updating the paths between the sources and destinations, the ant colony algorithm must be run, which needs a lot of processing and takes a long time. Therefore, in SAMQ, it is possible that the discovered routes have been disconnected, leading to a low performance in the average packet delivery ratio and lost packets. In OSTD, the discovered paths are more up to date than SAMQ. However, this method does not use an advanced method to select the paths. But the GSO algorithm requires less processing and time than the ant colony algorithm, and in the proposed algorithm, GSO is frequently executed to update routes. Therefore, the routes in GSO are more up to date than SAMQ. Moreover, the proposed algorithm uses the glowworms swarm algorithm, which is a powerful heuristic algorithm to select routes, and therefore, the selected routes in the proposed algorithm are better than the ones in OSTD, leading to a better performance in the average packet delivery ratio and the lost packets.

7. Conclusion

In this work, a routing protocol has been provided for VANETs based on the glowworm swarm optimization algorithm. Using the glowworm swarm optimization algorithm, the proposed algorithm detects the optimal route between three-way and intersections, and the packets are delivered based on the optimal routes. The simulation results show that the proposed algorithm has a better performance than the similar algorithms. Although the performance of the proposed algorithm is better than the other two algorithms OSTD and SAMQ, it should be noted that the GSO algorithm requires a large number of glowworm to build an optimal path. Therefore, the proposed algorithm is suitable for scenarios in which three-way and intersections are crowded. As a suggestion to improve this research work, we can say how the GSO algorithm must be changed to be better than the other similar algorithms in all scenarios.

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نشریه هوش مصنوعی و داده کاوی

یک الگوریتم مسیریابی جدید برای شبکه‌های موردی خودرویی براساس الگوریتم بهینه‌سازی کرم شب‌تاب

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چکیده:

شبکه‌های موردی خودرویی یک نوع خاص از شبکه‌های موردی متحرک هستند که در آن‌ها خودروها به‌عنوان گره‌ها در نظر گرفته می‌شوند. به علت تغییر زیاد در توپولوژی و قطعی مکرر ارتباط بین گره‌ها در این شبکه‌ها، طراحی یک الگوریتم مسیریابی برای انتشار پیام در این شبکه‌ها یک مسئله مشکل است. در این مقاله یک الگوریتم مسیریابی جدید براساس الگوریتم بهینه‌سازی کرم شب‌تاب برای این شبکه‌ها ارائه می‌شود. به‌وسیله الگوریتم کرم شب‌تاب، الگوریتم مسیریابی پیشنهادی مسیر بهینه در سه‌راه‌ها و چهارراه‌ها را پیدا می‌کند. سپس براساس مسیر بهینه انتخاب‌شده، بسته‌ها به مقصد تحویل داده می‌شوند. الگوریتم پیشنهادی به‌وسیله الگوریتم بهینه‌سازی کرم شب‌تاب که یک الگوریتم توزیع‌شده است، یک ارزشی را به هر مسیر تخصیص می‌دهد. سپس مسیری که ارزش بیشتری دارد، برای ارسال بسته از مبدأ به مقصد انتخاب می‌شود. نتایج شبیه‌سازی نشان می‌دهد که الگوریتم پیشنهادی کارایی بهتری نسبت به الگوریتم‌های مشابه دارد.

کلمات کلیدی: شبکه‌های موردی خودرویی، مسیریابی، الگوریتم بهینه‌سازی کرم شب‌تاب، محیط شهری، تأخیر تحویل داده.