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Optimized Geographic Routing in Mobile Ad Hoc Network Using Gray Wolf Optimization

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Abstract

The geographic routing protocol (GRP) in general seeks the location of sensor nodes to decide the routing path in mobile ad hoc network. This increases the routing overhead while finding the location of nodes. On other hand, the GRP undergoes location inaccuracy and routing void problem. In order to resolve this, in this paper, Gray Wolf Optimization (GWO) is used. This GWO is responsible for proper selection of nodes selected by GRP based on the parameters and selection criteria in order to forward the packets to the next forwarding nodes to reach its destination. The simulation is carried out effectively between the GWO-GRP and existing ACO and fuzzy based GRP with varying network densities. The simulation results show that the GWO-GRP method achieves reduced average delay, increased network lifetime and reduced energy consumption than other methods. Further, it avoids the problems associated with GRP i.e. the location inaccuracy and routing void problem.

Keywords: Geographic routing protocol, Gray Wolf Optimization, MANETs, Location Accuracy.

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1. Introduction

Geographic Routing Protocol (GRP) [1,2], also known as position-based routing, is an ad-hoc routing approach. GRP is based on the assumption that nodes know the location and immediate surroundings and that the source node knows where to go. GRP operates on the basis of information available with a node about its neighbors without routing tables.

GRP is a proactive routing protocol in which GPS locates the nodes in a source node that collects network information with limited overhead control. GRP is a custom MANET Routing Tool (OPNET) that uses the shortest geographical distance between source and destination. GRP is an optimized network engineering tool, where in order to optimize flooding, GRP uses quadrants.

But in certain scenarios, such as aviation sensor grids, the application expansion of wireless sensor networks results in the movement of sensor nodes. For wireless dynamic sensor networks, an additional overhead routing and overhead storage are required in the existing routing protocols based on location service algorithms. Furthermore, the node position obtained is not precise enough, leading to a routing failure. Consequently, in existing geographic rutting protocols the high overhead problem and problem of location is also present various methods on GRP [5] – [11] is adopted, however, for the main part of geographical routing (greedy forwarding mode and transmission mode [3]), the void routing problem and network planarization problem [4] [17] [18] occur, resulting in a long path with a higher overhead.

To resolve this, the proposed system uses GWO algorithm to optimally select the sensor nodes, which are selected in prior by the GRP. This procedure is carried out in order to overcome the existing problem.

The main contribution of the paper includes the following:

- The GWO selects optimal nodes that are selected by GRP using the location of sensor nodes.
- GWO selects the nodes using the parameters and selection criteria in order to forward the packets via intermediate nodes to destination.

2. Proposed Method

In this section, the GRP is improved using GWO algorithm, where it requires an effective search in its solution space. This is often constructed using a novel fitness function, which is given by.

$$f_{\min}\left(x_i\right)=\alpha\left[\frac{d\left(e+1\right)}{e^{\frac{L}{Q}+1}}\right]+\left(\frac{1-\alpha}{PDR}\right) \quad (1)$$

where

d is the end to end delay,

L is the link quality between two different nodes,

Q is maximum link quality in the network,

PDR is defined as the packet delivery ratio and

α is defined as a constant with 0.5.

The proposed fitness function has the objective to reduce end to end delay and increase PDR. Based on requirement D can be changed.

2.1 Gray Wolf Optimization

The GWO (Figure 2) avoids the void nodes and that reduces the total number of hops to transmit the packets from source to destination. This avoids the routing void problem in MANETs. The GWO algorithm imitates hierarchy of leadership and a gray wolf hunting mechanism. To simulate the leadership hierarchy, four types of grey wolves, such as alpha, beta, delta and omega. In addition, three major steps are carried out to optimize hunting, search for prey, encircle prey and attacking prey. The algorithm for the GWO is taken from [12] [13] [15] [16].

Step 1. Initialize the population X_i (i = 1, 2, … n) of GWO

Step 2. Initialize GWO parameters (a, A, C)

Step 3. Calculate the individual fitness value in the population

Step 4. Record the first, second and third best individual as X_α, X_β, X_δ

Step 5. While (t< maximum iteration number)

Step 6. For each individual

Step 7. Update the position of current individual

Step 8. End for

Step 9. Update a, A, C

Step 10. Calculate the fitness value of all individual in the population

Step 11. Update X_α, X_β, X_δ

Step 12. t = t + 1

Step 13. End While

Step 14. Return X_α

The GWO has high scanning ability to prevent the algorithm from falling optimally at the local level. The GWO can easily reach the correct compromise between exploration and operating capacity, thus resolving many complex problems effectively. The selection of optimal values by the GWO algorithm is given in Figure 1.

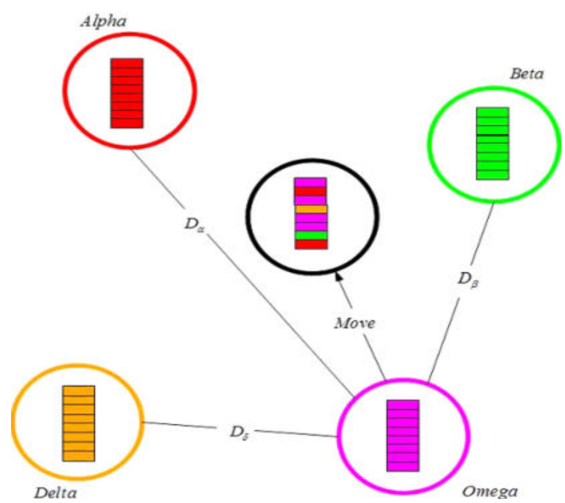

Figure 1. Position updating by GWO

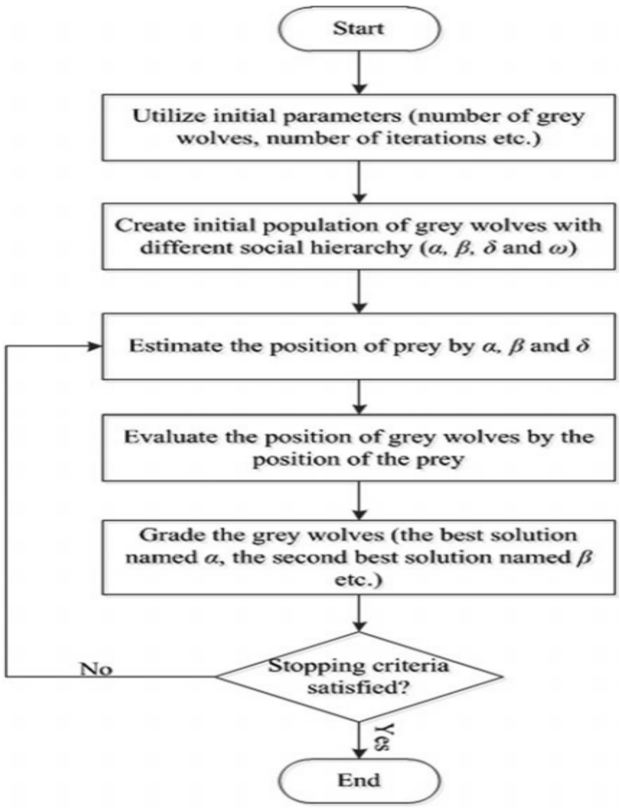

Figure 2. Process of GWO

2.2 Improved Geographical routing using GWO

In GWO-GRP protocol, the neighbor information is periodically maintained by sending Hello messages, where the steps for sending the packets via a node is given below:

Step 1. The data message is received at node *n* and it is updated at the location table of network node based on its location information of its sink and its past intermediate forwarding nodes. The processing of data message is done in application layer, if the node n is the sink and hence the routing ends. Now Go to step 2.

Step 2. The next forwarding node is selected by GWO algorithm by considering the neighbour information of a node n and if the sink is more than two hop neighbour nodes. Otherwise, the location information of sink and the node *n* is added with data message. The candidate node and its regions are found by the updated location of sink.

Step 3. If the candidate node is empty, go to step 6 and if it is not empty go to step 4.

Step 4. Evaluate the nodes using GWO algorithm in terms of its location, energy, neighbourhood node and network density and go to step 5

Step 5. Select the next forwarding node based on its ranking by the GWO or else discard the node and go for other nodes.

Step 6. Now forward the packets to the next neighbourhood nodes and check if the packets reach its destination.

3. Results and Discussions

The simulation is carried out using the network simulator. This method adopts the Random Way Point model with varying network densities between 50 and 500 in a two-dimensional area of 1000×1000 m^2. The velocity of each sensor node is operated between 10 and 40 m/s within 250m zone. The simulation parameters of the proposed method are given in Table.1.

Table 1. Simulation Parameters

Parameters	Values
Number of nodes	500
Speed	40m/s
Bit rate	1 Mbps
Application	UDP
Size	1000×1000 m^2

Table 2. Energy consumption

Number of nodes	Fuzzy-GRP	ACO-GRP	GWO-GRP
50	0.64	0.523	0.422
100	0.778	0.676	0.575
150	0.900	0.798	0.696
200	1.006	0.804	0.702

250	1.145	1.043	0.941
300	1.271	1.168	1.066
350	1.400	1.397	1.294
400	1.588	1.485	1.382
450	1.658	1.575	1.452
500	1.745	1.639	1.535

The Table 2 shows the results of energy consumption between the proposed GWO-GRP and existing ACO-GRP and Fuzzy-GRP. The results are simulated between the different node densities. The result shows that as the number of nodes in the network increases, the energy consumption tends to increase in each node. Hence, it is concluded that as the number of the nodes in the network increases, the lifetime of sensor nodes reduces due to increased computation for transmitting the packets between the source and destination nodes. Further, the proposed GWO-GRP offers reduced energy consumption than other methods, since the wolves performs best in iterating the individuals towards optimal results than ACO or fuzzy. The results obtained are considered to be in an improved manner.

Table 3. End-to-end delay

Number of nodes	Fuzzy-GRP	ACO-GRP	GWO-GRP
50	785.66	756.53	743.47
100	794.71	788.68	765.57
150	906.23	894.17	885.13
200	935.36	924.31	813.80
250	979.57	966.51	946.41
300	996.65	990.62	972.54
350	1019.76	1014.73	1006.69
400	1035.83	1027.79	1015.74
450	1066.98	1054.92	1038.84
500	1087.07	1078.03	1066.98

The Table 3 shows the results of average end-to-end delay between the proposed GWO-GRP and existing ACO-GRP and Fuzzy-GRP. The results are simulated between the different node densities. The result shows that the proposed method achieves reduced delay than other existing methods. It is seen from the results that as the number of nodes in the network increases, the delay in network increases. Since, the number of individuals in each iteration moves the required value to the optimal region, however, it takes some time to does it. Further, with increasing network density, the computation increases that is the other reason for increased average delay.

Table 4. Network Lifetime

Number of nodes	Fuzzy-GRP	ACO-GRP	GWO-GRP
50	65.91	68.96	71.87
100	68.90	71.40	74.21
150	70.19	73.00	76.24
200	72.80	76.04	80.38
250	76.10	80.40	82.89
300	79.96	83.09	85.43
350	82.41	86.56	88.75
400	85.78	91.39	90.03
450	90.15	94.19	92.05
500	91.85	96.52	96.31

The Table 4 shows the results of network lifetime between the proposed GWO-GRP and existing ACO-GRP and Fuzzy-GRP. The results are simulated between the different node densities. The results of simulation show that as the number of nodes in the network increases, the network lifetime tends to reduce. The increasing computation to find the optimal values tends to reduce the lifetime of each sensor nodes and that shortens the network lifetime. However, the results have shown that in proposed method, the wolves optimally find the values than other methods, which increases the lifetime of the network.

4. Conclusions

In this paper, we proposed GWO based geographic routing protocol that improves the network lifetime with optimal selection of nodes in GRP. The packets are routed effectively between the source and destination. In this method, the GWO is applied on GRP, where the initial set of sensor nodes for routing is selected by GRP and then the GWO selects the optimal number of nodes selected by GRP for routing. The routing effectively shows increased network lifetime with reduced delay, and reduced energy consumption than other methods.

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