A Hybrid Method Based on Genetic Algorithm and Ant Colony System for Traffic Routing Optimization

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Summary
The Ant Colony System (ACS) is a variant of Ant colony optimization algorithm which is well-known in Traveling Salesman Problem. This paper proposed a hybrid method based on genetic algorithm (GA) and ant colony system (ACS), called GACS, to solve traffic routing problem. In the GACS, we use genetic algorithm to optimize the ACS parameters that aims to attain the shortest trips and time through new functions to help the ants to update global and local pheromones. Our experiments are performed by the GACS framework which is developed from VANETsim with the ability of real map loading from open street map project, and updating traffic light in real-time. The obtained results show that our framework acquired higher performance than A-Star and classical ACS algorithms in terms of length of the best global tour and the time for trip.

Keywords:
Traffic routing; ant colony system; genetic algorithm; VANET simulator.

1. Introduction

Recently, traffic congestion has become one of the most serious problems in developing countries due to the rapid growth of their economy and population. Hence, the traveling salesman problem (TSP) which is famous problem on finding the shortest path has attracted a lot of researches on traffic routing optimization. A well-known method for solving the TSP is the ant colony optimization algorithm (ACO). There are some variants of ACO such as Ant system (AS) [1], Ant Colony System (ACS) [2] which show good efficiency on the shortest path problem. In order to improve the shortest path finding performance, the ACS uses new mechanisms based on three main innovations including tour construction, global pheromone trail update and local pheromone trail update [2]. Finding the optimal set of parameters for ACS plays an important role in this algorithm. The performance of the meta-heuristics methods is often dependent on the settings of their parameters which are highly attractive to many researchers. However, finding the suitable parameters for an algorithm is a nontrivial task in practice.

The adaptation approaches for setting parameters could be divided into offline and online procedures. Offline methods find appropriate parameter values before their deployment, while online methods modify them in solving problem. Thomas Stutzle et al. [3] has reviewed many researches on adaptation strategy to set up parameters in ACO variants. This review showed that the online method with small ant numbers gives better results, but it employs the fixed parameter setting method. In practice, the parameter values need to be variable when the algorithm applies to different cases. Marco Dorigo et al. [2] has built a new local updating rule for ACS and their obtained results showed a better performance than other heuristic algorithms. They demonstrated the importance of the ACS parameter values such as the ant number to attain a good result. However, the values in this study were manually chosen. Zhaoquan Cai et al. [5] proposed adaptive weight ACS parameters in which they built new computation method for parameter estimation including pheromone evaporation rate and heuristic information using the probability function. In another study, Jiping Liu et al. [4] combined genetic algorithm (GA) with ACS in which they used GA to optimize three parameters in transfer rule of tour construction, while other parameters were fixed. Dorian Gaertner et al. [6] developed a Genetically Modified Ant Colony System (GMACS), which also combines GA and ACS by fitness function, to produce improved solutions. Yet it did not show obvious relationship between ant number and the parameter set. Xianmin Wei. [7] suggested some good value for setting ant number. In fact, there are relationships between ant number with parameters and on themselves. However, there is not any manifest method to select a set of parameters homogeneously.

Besides the selected shortest path, time and conditions of environment such as width of road, traffic time light, potential congestion information are hence also very important in traffic routing optimization. In fact, additional conditions of traffic light and congestion information are essential factors in parameter estimation in

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the node on trips which therefore helps ants to choose a suitable node.

For this reason, we also propose a hybrid algorithm based on GA and ACS (GACS) for traffic routing optimization. In proposed method, GA is used to optimize parameters of ACS with new functions that are used for updating pheromone to acquire not only the shortest trip but also the shortest time. We simulated and visualized GACSS framework on real map, which could change the conditions online. The results obtained from our experiment are compared with other algorithms such as A-Star, classical ACS and they showed that the proposed GACS is more effective than the others. It is not only shorter length but also smaller time for trip.

The remainder of the paper is organized as follows: Section 2 gives a description of proposed hybrid algorithm for traffic routing. Section 3 presents the simulation experiments and results. Finally, some conclusions are given in section 4.

2. A Hybrid Framework for Traffic Routing

2.1 The Genetic Algorithm

Genetic algorithms (GA) are search methods based on principles of natural selection and evolution processes [8]. *The GA is applied in two primary areas of research: optimization, in which GAs represent a population based optimization algorithm and adaptation in complex systems.* The basic principle of genetic algorithm is following these steps [9]:

- Step 1: Initialization, the initial population of candidate solutions (chromosomes) is randomly generated across the search space.
- Step 2: Evaluation, once the population is initialized or an offspring population is created, the fitness values of the candidate solutions are evaluated.
- Step 3: Selection, the selection step allocates more copies of those solutions with higher fitness values and thus imposes the survival-of-the-fittest mechanism on the candidate solutions.
- Step 4: Recombination, the recombination step combines parts of two or more parental solutions to create better new possible solutions.
- Step 5: Mutation, while the recombination operates on two or more parental chromosomes, the mutation randomly modifies a local solution. Again, there are many variations of mutation, but it usually involves one or more changes to be made to an individual's trait or traits.
- Step 6: Replacement, the offspring population created by selection, recombination, and mutation replaces the original parental population.
- Step 7: Repeat steps 2-6 until a terminating condition is met.

In our proposed GACS framework, GA is used to find the best set of parameter values for ACS.

2.2 The Ant Colony System (ACS)

The ACS is a variant of ant system with improved efficiency in finding the shortest path [2]. The ACS is based on three main parts as follows:

- Tour construction of Ant colony system: *In ACS, we use the initial parameter and compute values*. An ant k in node i chooses the next node j with a probability defined by the random proportional rule as follows:

$$p_{ij}^{k}(t)=\frac{\left[\tau_{ij}(t)\right]^{\alpha}.\left[\eta_{ij}\right]^{\beta}}{\sum_{l\in N_i^k}\left[\tau_{il}(t)\right]^{\alpha}.\left[\eta_{il}\right]^{\beta}},\quad \text{if } j\in N_i^k \qquad (1)$$

where N_i^k is its feasible neighborhood, $\eta_{ij}=1/d_{ij}$ is a *priori* available heuristic value and d_{ij} is the distance between city i and city j, $\tau_{ij}(t)$ is the pheromone trail on the arc (i, j). The parameters α, β determine the relative influence of the pheromone trail and the heuristic information. In ACS, the random proportional rule with probability $q_0 \in [0, 1]$ for the chosen next city visit is defined as:

$$j=\begin{cases}\arg\max_{l\in N_i^k}\left\{[\tau_{il}]^{\alpha}[\eta_{il}]^{\beta}\right\}, & \text{if } q\le q_0;\\ J, & \text{otherwise;}\end{cases} \qquad (2)$$

where J is a random variable selected according to the probability distribution given by Eq. (1).

- Global pheromone trail update: In ACS, after each iteration, the shortest tour (global-best tour) of this iteration is determined, and arcs belonging to this tour receive extra pheromone, so only the global-best tour allow ants to add pheromone after each iteration by the global updating rule as follows:

$$\tau_{ij}(t+1)=(1-\rho)\tau_{ij}(t)+\rho\,\Delta\tau_{ij}^{gb}(t) \qquad (3)$$

with $\forall (i,j)\in$ global-best tour

where $\Delta\tau_{ij}^{gb}(t)=1/L^{gb}$, and L^{gb} is the length of the global-best tour. It is important to note that the pheromone trail update rule is only applied to the arcs of the global-best tour, not to all the arcs like in AS. The parameter ρ represents for the pheromone evaporation.

- Local pheromone trail update: In addition to the global update rule, the ants use a local update rule that is immediately applied after visiting an arc during the tour construction in ACS. The local update rule is defined by the function below:

$$\tau_{ij} = (1-\xi).\tau_{ij} + \xi.\tau_0 \tag{4}$$

where the pheromone decay coefficient ξ ($\xi \in$ [0, 1]), and τ_0 are two parameters of ACS algorithm. The value of τ_0 is set to be the same as the initial value of the pheromone trails. A good value of τ_0 can be computed as $1/\left(n.L^{nn}\right)$, where n is the number of cities in the TSP instance and L^{nn} is the length of the nearest-neighbor tour. When one ant uses an arc (i, j) each time, its pheromone trail τ_{ij} is reduced, so that the arc becomes less desirable for the following ants.

2.3 The Hybrid Method Based on Genetic Algorithm and Ant Colony System (GACS)

In traffic routing problem, heuristic information of environment is highly significant to help ants not only to find the shortest tour but also to save time and to realize congestion potential roads. Therefore, we develop a hybrid method based on GA and ACS to solve the traffic routing problem that is called GACS algorithm.

Firstly, we define new functions to update global and local pheromones in ACS. The functions in the global and local pheromone trial update parts that we propose will consider some information including the length of tour, the average velocity, the delay time of traffic light, the number of traffic participants at one time which denotes the road density or congestion information. The local pheromone updating function is defined by function below

$$\tau_{ij} = (1-\xi).\tau_{ij} + \xi.\tau_0^j ; \tag{5}$$

$$\tau_0^j = \left(n.L^{nn}\right)^{-1} + d_{ij} + r_{ij} + v_{ij} \tag{6}$$

where d_{ij} represents the road density on arc from node i to node j and it is computed as $d_{ij} = a_{ij}/w_{ij}$ with a_{ij} is the ants on arc from node i to node j and w_{ij} as width of road from node i to node j; v_{ij} is the average velocity of ants on arc from node i to node j; r_{ij} represents the traffic capacity to solve congestion time and it is defined by $r_{ij} = a_{ij}/t_j$ with t_j is total delay time of traffic light signal at node j. Thus ant can perceive the traffic status on arc and the next node from d_{ij}, v_{ij}, r_{ij}.

In the global updating rule, our proposed function to improve our traffic routing results is defined as:

$$\Delta\tau_{ij}^{gb}(t) = \frac{1}{L^{gb}} + \frac{1}{V^{gl}} + \varphi\sum_{j=1}^{N-1} d_{jh} + \psi\sum_{j=1}^{N-1} r_{jh} \tag{7}$$

with $h = j + 1$, N is the total nodes on global best tour and ψ, φ are weighting factors, and V^{gb} is the average velocity on global – best – tour. The hidden information such as length, velocity, density and traffic light status is significant to updating pheromone for global best tour that aims to improve the traffic routing system. Together with the parameters α, β, q_0 in Tour Construction that directly affect to the next node selection of the ant, the parameters ρ, ψ, φ are very important to finding the best tour by ACS. Therefore it is necessary to suitably set these parameters.

Secondly, we combine GA with ACS to optimize the set of parameters ($m, \alpha, \beta, q_0, \rho, \psi, \varphi$) representing for chromosome. The GA is applied to choose the best values for chromosome through fitness evaluation of every chromosome. The fitness function of chromosome c is computed by below equation

$$f(c) = \frac{1}{L^{gb}} + V^{gb} + \sum_{j=1}^{N-1}(d_{jh})^{-1} + \sum_{j=1}^{N-1}(r_{jh})^{-1} + \frac{1}{t_c} \tag{8}$$

where t_c is total time on global best tour. The fitness function acquires a higher value when the quality of the chromosome is better than the others.

About the termination condition of genetic algorithm, we suppose the number of iterations of genetic algorithm is NL, then $NL_{\min} \le NL \le NL_{\max}$ with NL_{min} is the minimum iteration times of genetic algorithm and NL_{max} is the maximum iteration times of genetic algorithm. The flowchart of the proposed GACS algorithm showing a hybridization of GA and ACS in traffic routing optimization is shown in Fig. 1. In this flowchart, all steps of GA involve from the start until the termination condition met as a part of ACS to find the best set of parameters that is used to calculate the updating functions in ACS. Furthermore, the developed traffic routing framework based on GACS algorithm enables to change online the condition of traffic light system which is very important in traffic routing. In fact, the traffic light system is a useful factor on controlling traffic system that is really interesting in the development of intelligent transportation system [10]. The changing condition of traffic light such as adding a light or changing delay time light in our GACS framework can be considered as an online tuning method. After the conditions are varied, the GACS framework updates new status by updating pheromone functions defined in Eqs. (5-7).

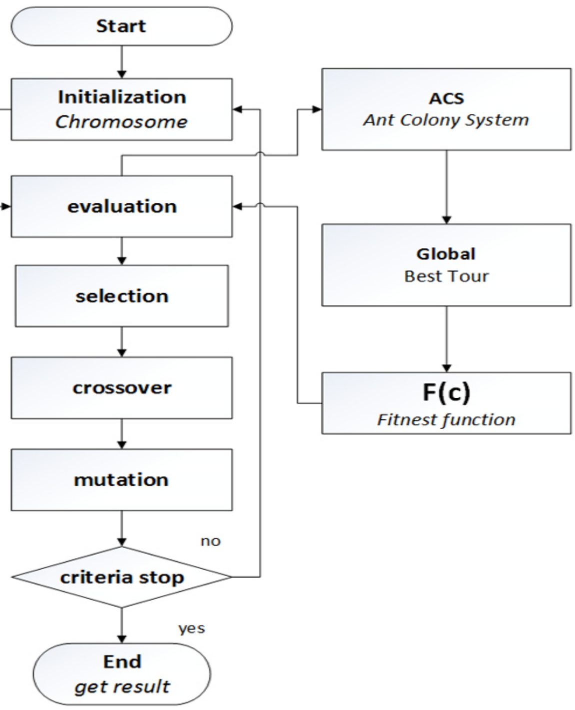

Fig. 1 Flowchart of the GACS algorithm.

3. Experiments and Results

3.1 Simulation of traffic routing with VANET simulator

The VANET simulators were developed to simulate Vehicular Ad-hoc Networks (VANET) [11, 12]. They could be classified as microscopic or macroscopic in terms of mobility model. In our simulation, microscopic traffic simulator is used that emphasizes local behavior of individual vehicles by representing the velocity and position of each vehicle at a given moment [13]. The VANET simulator has two main components including a network component and a vehicular traffic component. The network component is responsible for simulating the behavior of a wireless network, while the vehicular traffic component provides an accurate mobility model for the nodes. Mobility models represent the velocity and position of each vehicle at a given moment. This type of simulation is especially helpful to traffic routing problem.

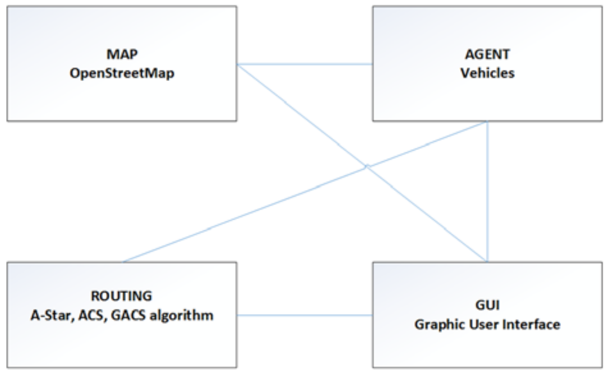

Fig. 2 VANET simulation system with routing algorithms.

The microscopic VANET simulator in traffic routing problem considers vehicles as distinct entities that could communicate and share information on traffic density, speed, moving direction of vehicles, road and traffic light. The simulation on VANET with GACS framework we develop includes four modules as shown in Fig. 2.

- MAP module processes the map problem to get and transform map from an open street map project, load and visualize agent activity. It also establishes online changing traffic conditions such as traffic light, road and traveling environment attributes.
- AGENT module constructs agents from types of traffic vehicles with attributes on system, controlling agent behaviors and traffic conditions.
- GUI module processes visualization graphic information and provides interaction ability between user and the system.
- Routing module processes algorithms and return the results to the system.

3.2 Experimental parameters

Based on the parameters analysis in [3, 7, 14, 15] which obtained remarkable results, the appropriate set of parameter value and the range of them are initially selected in our experiments. With chromosome $(m, \alpha, \beta, q_0, \rho, \psi, \varphi)$ of GACS algorithm via experiment it was shown that the appropriate range for α, ρ, q_0 is from 0 to 1, and β is between 1 and 5, and ψ, φ is between 1 and 10. At last, the initial ant number of system m is between 1 and 500. The fitness function is computed by Eq. (7) and the stopping criteria are NL_{min} = 10 and NL_{max} = 55.

The simulation experiments in this study run on Windows 7 OS, Intel Core i7-6700 (3.4 Ghz, 8M Cache) processor, 16GB DDR3L RAM. We used Open JDK Java 8 environment and VANETsim version 1.3 to develop our simulation framework. The types of vehicles include motorbike, bicycle, bus, with total number of them between 10 and 100. The performance of the system is evaluated by criteria such as total length of vehicle from starting point to destination, time for this trip and time that is used for algorithm processing. The results obtained from our framework are then compared to A-Star and ACS algorithms.

3.3 Results and Analysis

In the first scenario, we evaluated on city map of Berlin Germany, in which the data is loaded from open street map then it randomized starting point coordinate A as x = 582858 and y = 353950 on Holzmarktstrabe road and destination B on Littenstrabe with coordinate as x = 550418, y = 320967. The GACS framework selected the trip to travel from A to B as shown in Fig. 3(a). When the vehicles realize congestion at the intersections between StralauerStrabe and Littenstrabe, it updates information and chooses Direksenstrabe road direction to their trip. Experiment results are evaluated in terms of three values including Length (length of the global best tour), Time (time of best tour), Processed time (processing time of the system). The obtained results in this scenario are shown in Table 1 and they show that the proposed GACS algorithm outperforms the other algorithms in terms of Length and Time. In particular, the Length of the GACS algorithm is shorter than that of A-Star 515 meters and ACS 405 meters. The time for global best tour of the GACS is smaller than that of A-Star and ACS 6.76 seconds and 4.58 seconds respectively. The results are improved because the environment information is integrated to node and ants could perceive suitable node on their tour. Although, the processing time of the GACS algorithm is longer because the ACS algorithm in the hybrid algorithm has repeated computing on GA, it is acceptable in practical applications.

Table 1: Simulation A-star, ACS, GACS algorithm results on Berlin map

Algorithm	*Length (meter)*	*Time (seconds)*	*Processed Time (milliseconds)*
A-Star	1060	58.56	25
ACS	950	56.38	45
GACS	545	51.80	156

Fig. 3 Simulation GACCS framework on (a) Berlin Map, (b) Hanoi Map.

In second scenario, the framework is evaluated by the same method on city map of Hanoi, Vietnam with starting point in Tran Thai Tong street at coordinate A as x = 12971115, y = 10755648 and destination point B in Tho Thap street as x = 12991416, y = 10810560 as shown in Fig.3(b). The obtained results in this scenario are shown in Table 2. Similar to the first scenario, the GACS algorithm also outperforms the other algorithms in terms of Length and Time. However, Time value in this scenario is slightly longer than that in the first scenario that is because the traffic conditions of Berlin map are better than that of Hanoi map.

Table 2: Simulation A-star, ACS, GACS algorithm results on Hanoi map

Algorithm	*Length (meter)*	*Time (seconds)*	*Processed Time (milliseconds)*
A-Star	1150	64.12	18
ACS	802	60.88	31
GACS	601	58	162

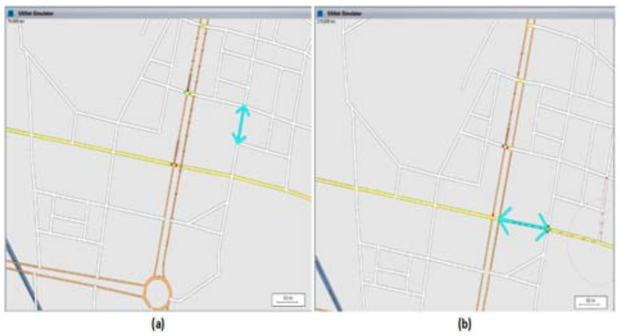

Fig. 4 Online monitoring traffic light.

In the third scenario, the framework is deployed in online setting of traffic light condition as shown in Fig. 4. Fig. 4(a) shows the ability to update traffic light system on Caugiay district in Hanoi Map. The traffic light was added and the delay time of traffic light was changed. Then the

GACS system updated and processed online information. The ants have chosen new suitable tour. It is really significant to apply our framework in practical cases which need to change traffic conditions to solve congestion problem.

4. Conclusion

In this paper, we proposed a hybrid framework, called GACS, for solving traffic routing problem in shortest path and time. The proposed GACS framework uses GA to optimize parameter settings of ACS. We have demonstrated via simulation experiments that the hybrid GACS algorithm outperforms A-star, ACS algorithms in terms of length and time of the best global tour. However, it has longer processing time than the other algorithms. Moreover, the GACS framework can provide the ability for online monitoring the condition of traffic light. In the future, we are planning to further improve the current framework about the ability of dynamic changing the traffic light and reducing the processing time.

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