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

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Received 18 April 2019; Revised 06 July 2019; Accepted 06 July 2019

Abstract: This paper presents a hybrid method that combines the genetic algorithm (GA) and the ant colony system algorithm (ACS), namely GACS, to solve the traffic routing problem. In the proposed framework, we use the genetic algorithm to optimize the ACS parameters in order to attain the best trips and travelling time through several novel functions to help ants to update the global and local pheromones. The GACS framework is implemented using the VANETsim package and the real city maps from the open street map project. The experimental results show that our framework achieves a considerably higher performance than A-Star and the classical ACS algorithms in terms of the length of the global best path and the time for trips. Moreover, the GACS framework is also efficient in solving the congestion problem by online monitoring the conditions of traffic light systems.

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. In fact, the traffic routing optimization problem is an important issue all over the world. There are various approaches to deal with this issue that depend on the complexity of problems and the related parameters.

A well-known approach for solving above problem 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 shows good efficiency on the optimal path problem with traffic congestion parameters. In order to improve the performance in finding the optimal path, ACS uses new mechanisms based on three main innovations including paths construction, global pheromone trail update and local pheromone trail update [2-6]. Most of existing studies focus on finding the optimal parameters for ACS to achieve the better results with reasonable efforts. However, finding the suitable parameters for an algorithm is a nontrivial task in practice.

The adapting approaches for setting parameters could be divided into offline and online procedures. The offline methods find appropriate parameter values before their deployments, while online methods optimize those on the way. Stutzle et al. [7] reviewed a number of studies on their adaptation strategy to set up parameters in ACO variants. It has been shown that the online methods with small ant numbers and fixed parameter setting often lead to a better performance. However, this is not realistic because the parameter values might change when applying the algorithm into different cases. Dorigo et al. [2] has built a new local updating rule for ACS which obtained a better performance than the other heuristic algorithms. They demonstrated the importance of the ACS parameters, for instance the optimal number of ants. However, the parameter values in this study were manually chosen. Zhaoquan Cai and Huang [8] proposed an adaptive weight ACS parameters in which they built the novel computation method for parameters estimation including pheromone evaporation rate and heuristic information using the probability function. In another study, Liu et al. [9] combined genetic algorithm (GA) with ACS in which they used GA to optimize three parameters in transferring rule of path construction, while other parameters were fixed. Gaertner and Clark [6] developed a Genetically Modified Ant Colony System (GMACS), which also combines GA and ACS by a fitness function to gain the better performance. But it does not show the obvious relationship between the number of ants and the rest parameters. Wei [11] suggested some good tricks for setting the number of ants. Actually, we all knew that there are some unknown relationships among parameters. However, there are no manifest references to find those parameters effectively.

Hence, an approach to automatically determine the optimal combination of the ACS parameters is desirable for a given traffic routing problem. It is more significant in the practical application of the ACS algorithm for developing an intelligent transportation system where the finding the optimal path required many input information such as road conditions, vehicle type, traffic conditions and so on. Such information can be collected from various sources consisting of public or private organizations. For the path-finding problem based on information from drivers, each driver plays a role of an ant in the ant colony. The driver can find the best path to the destination based on the ACS algorithm. However, the expected result strongly depends on the setting of the parameter values. Therefore, the parameter adaptation plays an important role in obtaining the best solution of traffic routing optimization problem.

In this paper, we propose a hybrid algorithm based on GA and ACS (namely GACS) for traffic routing optimization. GA is used to optimize the parameters of ACS with novel functions for updating pheromone to acquire not only the best trip but also the shortest travelling time. Moreover, we also consider solving finding the best route problem by the GACS algorithm under the congestion and the automatically condition changes of the traffic light system. We simulated and visualized the GACS framework on a real map, which could change the conditions online. The experimental results of our proposed method are compared with others such as A-Star, the classical ACS. It has been shown that our method is able to achieve a higher and more effective performance than others in the same conditions.
The rest of the paper is organized as follows: Section 2 gives a description of the 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 algorithm (GA) is a search and optimization method based on the principles of natural selection and evolution processes [12]. The basic principle of genetic algorithm follows the following these steps [13]:

Step 1 (Initialization) the initial 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.

By building a suitable fitness function, GA can be applied to look for optimal parameters of ACS algorithm. The ants with the best fitness are selected to produce offspring of the next generation. The worst ants’ parameters will be replaced by the produced ants’ parameters.

2.2. The ant colony system (ACS)

The ACS is a variant of ant system with an improved efficiency in finding the best path with given conditions [2]. The ACS is based on three main processes as follows:

a. Path construction of Ant colony system: An ant \( k \) in node \( i \) chooses the next node \( j \) with a probability defined by the random proportional rule as follows:

\[
p^k_{ij}(t) = \frac{\left( \tau_i(t) \right)^{\alpha} \left( \eta_{ij} \right)^{\beta}}{\sum_{l \in \Lambda(N_i)} \left( \tau_l(t) \right)^{\alpha} \left( \eta_{lj} \right)^{\beta}}, \quad \text{if } j \in N_i^k \tag{1}
\]

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 point \( i \) and point \( j \). The parameters \( \alpha \), \( \beta \) 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 point visiting is defined as:

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

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

b. Global pheromone trail update: In ACS, after each iteration, the global-best path of this iteration is determined, and the arcs belonging to this path receive extra pheromone, so only the global-best path allows ants to add pheromone after each iteration by the global updating rule as follows:

\[
\tau_{ij}(t+1) = (1-\rho) \tau_{ij}(t) + \rho \Delta \tau^{gb}_{ij}(t) \tag{3}
\]

for \( \forall (i,j) \in \text{global-best path} \)

where \( \Delta \tau^{gb}_{ij}(t) = 1/L^{gb} \), and \( L^{gb} \) is the length of the global-best path. It is important to note that the pheromone trail update rule is only applied to the arcs of the global-best path, not to all the
arcs like in AS. The parameter $\rho$, $0 \leq \rho \leq 1$, represents for the pheromone evaporation rate.

c. 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 path construction in ACS. The local update rule is defined by the function below:

$$\tau_{ij} = (1 - \xi) \tau_{ij} + \xi \tau_0$$  \hspace{1cm} (4)

where the pheromone decay coefficient $\xi$ ($\xi \in [0, 1]$), and $\tau_0$ are two parameters of ACS algorithm. The value of $\tau_0$ is set to be the same as the initial value of the pheromone trails and could be set as $1/(nL^m)$, where $n$ is the number of arcs, $L^m$ is the length of global path. So that, when one ant uses an arc $(i, j)$ each time, its pheromone trail $\tau_{ij}$ is reduced, so that the arc becomes less desirable for the following ants.

Thus, there are many parameters which affect the performance of the ACS in finding the best path. As above mentioned, adapting the set of parameters $(m, \alpha, \beta, q_0, \rho)$ can improve the performance of the ACS.

2.3. The hybrid method based on genetic algorithm and ant colony system (GACS)

In traffic routing problem, heuristic information of transportation environment is highly significant to help ants not only to find the best path but also to save time and to realize potential congestion 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 a number of novel functions to update global and local pheromones in ACS. The functions in the global and local pheromone trial update processes that we propose will consider some information including the length of path, the average velocity, the delay time of traffic light, the number of commuters at one time which denotes the road density or congestion information. The local pheromone updating function is defined by the function below

$$\tau_{ij} = (1 - \xi) \tau_{ij} + \xi \tau_0'$$  \hspace{1cm} (5)

$$\tau_0' = (nL^m)^{-1} + (d_{ij})^{-1} + (r_{ij})^{-1} + v_{ij}$$  \hspace{1cm} (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 vehicle number on arc from node $i$ to node $j$ and $w_{ij}$ is the width of road from node $i$ to node $j$; $v_{ij}$ is the average velocity of vehicles 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 the total delay time of traffic light signal at node $j$. The pheromone deposited by ants is increased on the visited arcs where the $d_{ij}$, $r_{ij}$ values are lower and the $v_{ij}$ value is higher. Thus vehicles 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:

$$\Delta \tau_{ij}^h(t) = \frac{1}{L^h} + V^h + \phi \frac{\sum_{j=1}^{N} (d_{ij})^{-1} + \psi \sum_{j=1}^{N} (r_{ij})^{-1}}$$  \hspace{1cm} (7)

with $h = j + 1$, $N$ is the total nodes on global best path and $\psi$, $\phi$ are weighting factors, and $V^h$ is the average velocity on the global - best - path. The hidden information such as the length, velocity, density and traffic light status is significant to updating pheromone for the global best path that aims to improve the traffic routing system. Together with the parameters $\alpha, \beta, q_0$ in Path Construction that directly affect to the next node selection of the ant, the parameters $\rho$, $\psi$, $\phi$ are very important to finding the best path by ACS. Therefore, it is necessary to set these parameters appropriately.

Secondly, we combine GA with ACS to optimize the set of parameters $(m, \alpha, \beta, q_0, \rho, \psi, \phi)$ 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

$$f(c) = \Delta \tau_{ij}^h + \frac{1}{t_e}$$  \hspace{1cm} (8)
Then, Eq. (7) is substituted into the fitness function of chromosome $c$, we get:

$$f(c) = \frac{1}{L} + V \phi \sum_{j=1}^{N} (d_{ji})^{-1} + \psi \sum_{j=1}^{N} (r_{ji})^{-1} + \frac{1}{t_c} \tag{9}$$

where $t_c$ is the total time on global best path. After each chromosome $c_k$ is generated by the GA, the ACS is implemented to evaluate the corresponding fitness function $f(c_k)$. The best set of parameters that corresponds to the best path can be determined by $c_{best} = \max(f(c_k))$, $k = 1, \ldots, N$. The fitness function acquires a higher value when the quality of the chromosome is better than the others.

![Flowchart of the GACS algorithm](image)

Figure 1. The flowchart of the GACS algorithm.

About the termination condition of genetic algorithm, we suppose the number of iterations of genetic algorithm is $NL$, then $NL_{\text{min}} \leq NL \leq NL_{\text{max}}$ with $NL_{\text{min}}$ is the minimum iteration times of genetic algorithm and $NL_{\text{max}}$ 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 Figure 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. The parameters of ACS are randomly initialized in a given range. Furthermore, the developed traffic routing framework based on the 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 [14, 15]. 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 changed, the GACS framework updates new status by updating pheromone functions defined in Eqs. (5-7). The online parameters adaptation in the GACS framework results in an improved performance of the traffic routing optimization.

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) [16, 17]. They could be classified as microscopic or macroscopic in terms of mobility model. In our simulation, the microscopic traffic simulator is used that emphasizes local behavior of individual vehicles by representing the velocity and the position of each vehicle at a given moment [18]. 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 the position of each vehicle at a given moment. This type of
simulation is especially helpful to traffic routing problem.

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 Figure 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 the algorithms and returns the results to the system. In this module, beside the proposed GACS algorithm, the A-Star and ACS algorithms are also used for performance comparison.

3.2. Experimental parameters

Based on the parameters analysis in [7, 11, 19, 20] which obtained remarkable results, the appropriate set of parameter values and their range of values are initially selected in our experiments. With chromosome \((m, \alpha, \beta, q_0, \rho, \psi, \phi)\) of GACS algorithm via experiments it was shown that the appropriate range for \(\alpha, \rho, q_0\) is from 0 to 1, and \(\beta\) is between 1 and 5, and \(\psi, \phi\) 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. (9) and the stopping criteria are \(NL_{\text{min}} = 10\) and \(NL_{\text{max}} = 55\).

The simulation experiments run on Windows 7 OS, Intel Core i7-6700 (3.4 Ghz, 8M Cache) processor, 16GB DDR3L RAM. Our simulation framework is developed using Open JDK Java 8 environment and VANETsim version 1.3. The types of vehicles include motorbike, bicycle, car and bus, with total number of them between 10 and 100. The performance of the system is evaluated by criteria such as the total length of vehicle from starting point to destination, the time for this trip and the 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 the city map of Berlin, Germany, in which the data is loaded from open street map, then it randomized the starting point \(A\) with coordinate as \(x = 582858\) and \(y = 353950\) on Holzmarktstrasse road and destination \(B\) on Littenstrasse with coordinate as \(x = 550418, y = 320967\). The GACS framework selected the trip to travel from \(A\) to \(B\) as shown in Figure 3(a). When the vehicles meet congestion at the intersections between StralauerStrasse and Littenstrasse, they reroute the path with updated information. The new routing will be changed to the Direksenstrasse road to complete their trip. Experimental results are evaluated in terms of three values including Length (the length of the global best path), Time (the time of best path), Processed Time (the 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, Length of the GACS algorithm is shorter than that of A-Star 515 meters and ACS 405 meters. The time for global best path of the GACS is smaller than that of A-Star and ACS 6.76 seconds and 4.58 seconds respectively. The performance of the GACS is improved because the environment information is integrated into nodes and ants could perceive the suitable node on their path. Although the processing time of the GACS algorithm is longer due to the repetition in calculation of the GA in ACS, it is still acceptable in practice.

### Table 1. Simulation 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                           |

In second scenario, the framework is evaluated by the same method on city map of Hanoi, Vietnam with the starting point A in Tran Thai Tong street at coordinate as x = 12971115, y = 10755648 and destination point B in Tho Thap street at coordinate as x = 12991416, y = 10810560 as shown in Figure 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 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                           |
Figure 4. Online monitoring traffic light.

In the third scenario, the framework is deployed in online setting of traffic light condition as shown in Figure 4. Figure 4(a) shows the ability to update traffic light system on Caugiay district in Hanoi Map. The traffic light is added and the delay time of traffic light is changed. Then the GACS system updated and processed online information. By adding a given delay time of traffic light, the fitness value of chromosome changes correspondingly in finding the optimal parameters based on GA. Subsequently, the pheromone updating of ants on the arcs is also changed to find the best path based on ACS. The ants consequently choose a newly suitable path. It is really significant to apply our framework in practical cases, which need to change traffic conditions to solve congestion problem.

Figure 5. Simulation on various transportation conditions.

Therefore, the framework is applied in the fourth scenario to simulate a situation of transportation system in congestion condition. In this scenario, the number of vehicles is increasing from 0 to 1500 vehicles which consist of cars, motorbikes and bicycles in order to see when congestion happens due to increase in the road density overtime. The various types of vehicles travelling at different speeds are visualized by different colored dots on the map. These vehicles are randomly distributed on the Nguyen Chi Thanh road, on Hanoi map, travelling between the coordinate of the point A (x = 21.030053, y = 105.812800) and the coordinate of the point B (x = 21.014934, y = 105.804353) as shown in Figure 5. This road is chosen in this simulation because it is where the traffic jams often occur at rush hours. Efficiency of the GACS framework in solving congestion problem is estimated in various transportation situations: normal, light traffic jam and heavy traffic jam which correspond to the situations that vehicles can go with the speed being less than or equal the maximum, half, and 10% of the speed limitation respectively. The obtained results are shown in Table 3. The normal transportation situation is specified when the vehicles are travelling without any collision, while the light congestion is specified when collisions occur at intersections (nodes). The heavy congestion is
specified when the vehicles start to be unmovable due to collisions.

Table 3. Simulation results on transportation conditions

| Algorithm/Status | Normal (minute) | Light congestion (minute) | Heavy congestion (minute) |
|------------------|-----------------|---------------------------|--------------------------|
| A-Star           | From 0 to 16 minutes | From 17 minutes to 24 minutes | To 25 minutes |
| ACS              | From 0 to 30 minutes | From 35 minutes to 40 minutes | To 45 minutes |
| GACS             | From 0 to 36 minutes | From 47 minutes to 58 minutes | To 60 minutes |

Thus, the efficiency of the path finding algorithm is proportional to the duration to maintain the normal status or the transition duration between statuses. The results in Table 3 show that the proposed GACS algorithm can extend the normal status that is 6 minutes and 19.5 minutes longer than that of ACS and A-Star algorithms respectively. The time period from the light traffic jam status to the heavy traffic jam status is also extended for the GACS algorithm. In particular, it is 15 minutes and 35 minutes longer than the ACS and A-Star algorithms respectively. This extension is resulted by dynamic adjustment of information updating in the GACS framework that is useful in traffic routing optimization. This simulation allows the managers and planners to evaluate the transportation system based on the data collected from personal devices to reduce the traffic congestion through changing transport conditions such as adding the traffic lights and adjusting the delay time of traffic light.

4. Conclusion

In this paper, we proposed a hybrid framework, named GACS to solve traffic routing problem in terms of distance 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 compared to A-star and ACS algorithms. However, it took longer processing time than those algorithms. Moreover, the GACS framework can provide the ability for online monitoring the condition of traffic lights. In the future, we are planning to further improve the current framework in order to dynamically change the traffic lights and reduce the processing time.

Acknowledgements

This research was funded by Vietnam National University, Hanoi (VNU) under the project no. QG 17.39.

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