



Consideration of Genetic Algorithm with Virus Infection solving Traveling Salesman Problem

Takuya Inoue, Yudai Shirasaki, Yoko Uwate and Yoshifumi Nishio

Tokushima University
2-1 Minami-Josanjima, Tokushima 770-8506, JAPAN
Email: {t-ionue, shirasaki, uwate, nishio}@ee.tokushima-u.ac.jp

Abstract

Genetic Algorithm (GA) is known as method to solve Traveling Salesman Problem (TSP). However, GA needs amount of time for finding approximate solution. Thus, this study proposes Genetic Algorithm with Virus Infection (GAVI). GAVI algorithm is using Virus Theory of Evolution (VTE) to be based on Genetic Algorithm (GA). GA can evolve by natural selection, while VTE can evolve by virus infection. GA characteristic convey informations to next generation by crossover. On the other hand, VTE characteristic has sharing of information among same generation. GAVI is using both these characteristics of GA and VTE. We apply GAVI to TSP and confirm that GAVI obtains more effective result than GA.

1. Introduction

Traveling Salesman Problem (TSP) [1] is known as one of the combinatorial optimization problems. When Salesman tours all cities at once, TSP is the problem of finding minimum total between each city distance in route. Then n is the number of cities in TSP, total route number increase at rate proportional to many of the factorial of n . Therefore, exploring total route number needs amount of time for finding approximate solution, however we would like to obtain the approximate solution in TSP quickly. It is necessary to solve the TSP in other ways except exploring total routes. Finding approximate solution method of TSP is a variety of ways.

Genetic Algorithm (GA) [2], [3] is one of the popular method in variety of ways to solve the TSP and is studied by many researchers all over the world. GA is modeling behavior of evolution in organic. Thus, GA is to explore the solution for repeating crossover on the basis of organic evolution. Organic evolution is to survive individuals with high evaluation in alternation of generations. Thus, GA can obtain the approximate solution by overlaying the generation. However, evolution needs large number of alternation of generations. Thus, GA needs amount of time and convergence speed is slow.

In this study, we propose Genetic Algorithm with Virus

Infection (GAVI). GAVI is using Virus Infection algorithm based on GA. One of the characteristics of the Virus Infection [4]-[6] is infection other same generations at once. This characteristic seems to be useful for finding the approximate solution quickly. Therefore, we consider that the virus will help to solve the TSP. We carry out computer simulations for various parameter values and confirm that the proposed algorithm achieves better performance than the conventional GA.

2. Virus Theory of Evolution

Organic evolution is theory based on natural selection. In natural world, high fitness individuals organism survive, while low fitness individuals organism become extinct. Over the years, only higher fitness individuals survive. We call it Evolution. Thus, evolution need to overlay generations.

On the other hand, there is theory that Virus Theory of Evolution (VTE) [7]. This theory is based on the evolution by Lateral Gene Transfer (LGT) [8] in Virus infection. LGT is uptake of the gene that occur between other individuals and among other species. Without evolution inherited from parent cell to child cell, genes can evolve. Low fitness individuals possibly evolve into high fitness individuals in just one generation by LGT in Virus infection. In other words, we assume that each individual become a better evaluation value quickly. Thus, we assume using VTE algorithm leads the approximate solution in less time and VTE theory is efficient in TSP.

3. Genetic Algorithm with Virus Infection

Selection, Crossover and Mutation are the main functions of the GA. GAVI is a method of VTE algorithm in Virus infection to be based on GA. Flow chart of GAVI shows Fig. 1. t_{max} is number of repeating times. GAVI algorithm is indicated the following Step1-7. Step2-7 is repeated until the set number of Crossover times. After the set number of Crossover times, GAVI output the best solution in all getting solutions.

step1 (Initialization)

Initialization is random route selection. Number of random route selection is U .

step2 (Evaluation)

Evaluation is defined by the following formula.

$$f_i = \frac{1}{d_i} \quad (1)$$

where d_i is total distance of each route and f_i is evaluation value. If d_i is low, f_i is high by this formula.

step3 (Selection)

Route is selected with a probability of p_i . p_i is defined by the following formula.

$$p_i = \frac{f_i}{\sum_{i=1}^n f_i} \quad (2)$$

where n is the number of cities. Selection is the method of tends to be chosen high evaluation route. Low evaluation route is chosen a few. Selection works that high fitness individuals organism survive, while low fitness individuals organism become extinct.

step4 (Fulfill crossover condition)

This section evaluates crossover condition. If parents is not fulfill crossover condition, crossover is not action. when crossover condition is fulfill, crossover is action.

step5 (Crossover)

Crossover is to be mated the two routes. In this study, we apply sub tour exchange crossover. This way makes a search for sub tour of Both Parent A and Parent B in common. If it does not find sub tour in common, crossover is not action. For example, between 1, 2, 5, 6 and 5, 1, 6, 2 are sub tour in Fig. 2. 1, 2, 5, 6 and 5, 1, 6, 2 are differ in line, however these are same class. Sub tour in 1, 2, 5, 6 can express 1, 2, 5, 6 and 6, 5, 2, 1, 5, 1, 6, 2 can express 5, 1, 6, 2 and 2, 6, 1, 5. Because two expressing are same about total route distance in Fig. 3. Thus, after crossover, four child exist.

step6 (Infection)

We define elements of each route as Virus, elements select the best route in obtain and part of each route is infected by this Virus at random. Number of element selects is fixed probability.

For example, 3, 5 is a virus and has infected the route of 6, 1, 3, 5, 2, 4 in Fig. 4. *Infection* part determines 1, 4 in the

route. The route replace to 3, 5 1, 4. We call it *Infection*. *Infection* is incorporating partial optimum solution.

step7 (One route reset in random)

If a obtained solution is same among number of s , one route in all routes is initialization in random. $O(t)$ is the obtained solution in number of t times, while $O(t-s)$ is obtain solution previous number of s . Thus, $O(t) = O(t-s)$ shows that the obtained solution is same among number of s . We assume that this is efficient to escape local minimum.

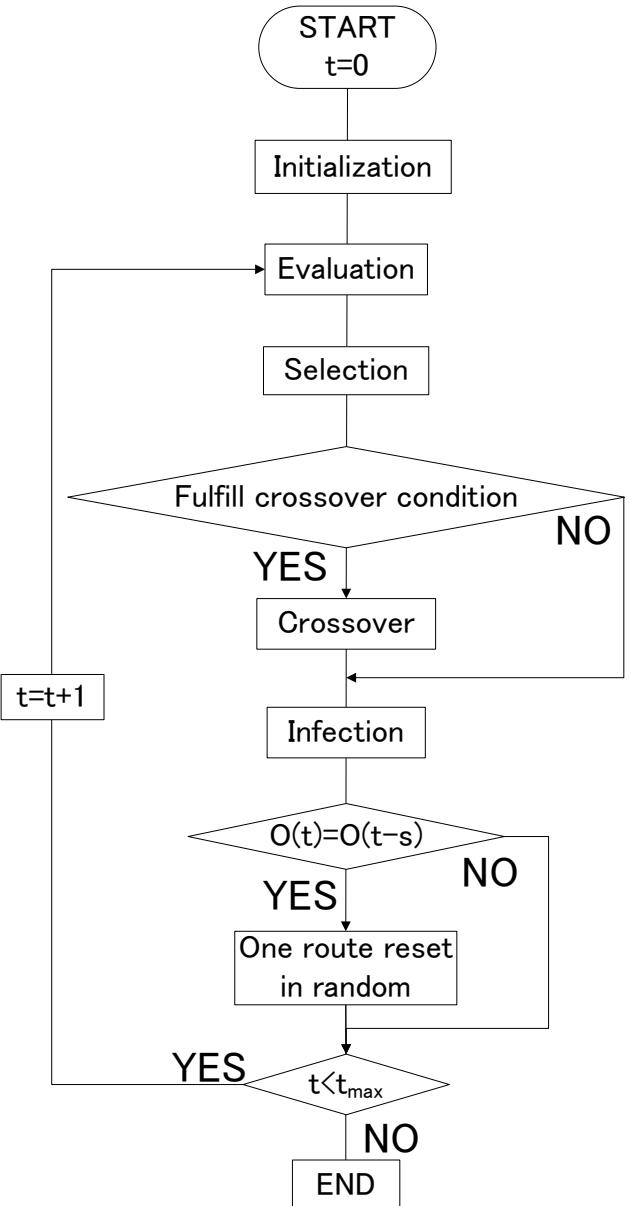


Figure 1: Flow chart of GAVI.

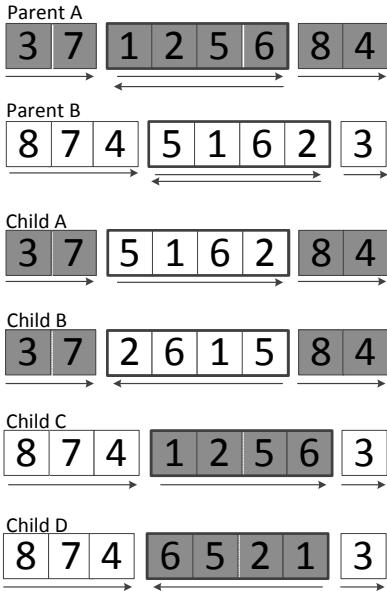


Figure 2: The mechanism of *Infection*.

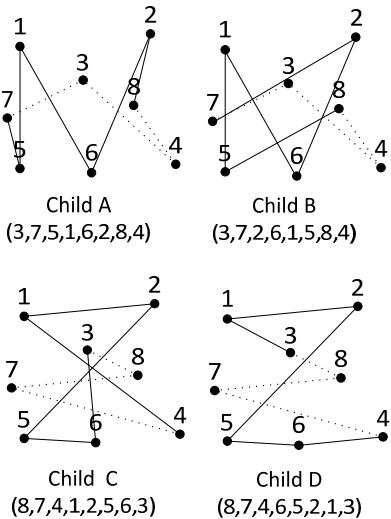


Figure 3: The mechanism of *Infection*.

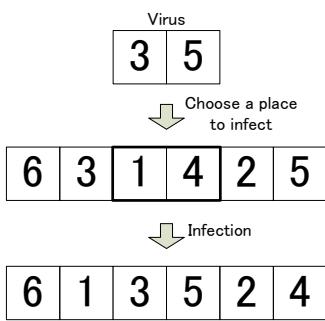


Figure 4: The mechanism of *Infection*.

4. Experimental Results

In order to compare the performance of GAVI and GA, we apply GAVI and GA to find approximate solutions in TSP such as att48 (48 cities). In this study, $t_{max} = 5000$, the number of simulation is 10 times, $U = 1000$, and *error rate* is defined by the following formula.

$$\text{Error rate}[\%] = \frac{(\text{obtain}) - (\text{optimum})}{(\text{optimum})} \times 100 \quad (3)$$

where *obtain* is minimum solution and *optimum* is optimum solution. When *obtain* value approaches *optimum* value, *Error rate* is low. For example, when *obtain* value is equally *optimum* value, *Error rate* is 0[%]. If *Error rate* is 0[%], we would obtain optimum solution. However, if *obtain* is bad solution, *error rate* is high. In Table 1-3, Ave is the average, Max is the maximum value and Min is the minimum value.

Table 1 shows the result of GA and Tables 2-3 show the result of GAVI. *Mutation* is to change the route with a certain probability and less likely to fall into local minimum. *Mutation rate* shows performing the *Mutation* probability. Table 2 uses value of $s = 100$, while Table 3 uses value of $s = 50$. GAVI can find a good solution by *Infection* from result of Tables 1-3. The best result of GA in Ave uses value of *Mutation rate* = 0.05, while the best result of GAVI uses value of *Infection rate* = 0.30 and $s = 100$.

Figure 5 shows error curves in each the best result of GA and GAVI. In Fig. 5, convergence speed of GAVI is faster than GA. During $t = 0 - 5000$, the result of GA and GAVI are most of the same. However, during $t = 1000 - 5000$, the result of GA is almost unchanged, while GAVI changes good solution by gradation. Thus, result of GAVI is better than GA.

Figure 6 shows relationship between *infection rate* and *error rate*. In Fig. 6, when *infection rate* is high and low, result is bad. In *infection rate* = 0.20, 0.30, 0.40, the result of GAVI is relatively good solution in both $s = 100$ and $s = 50$.

All results of GAVI are not better than GA in Tables 1-3. However, we assume that the result of GAVI is good by using appropriate *infection rate* in Fig. 6.

Table 1: The result of GA for 48 cities

Algorithm type	Mutation rate	Error rate[%]		
		Max	Min	Ave
GA	0.02	6.486	0.597	2.878
	0.05	3.618	0.559	2.266
	0.10	4.520	0.691	2.329
	0.20	13.938	0.250	2.708

Table 2: The result of GAVI for 48 cities ($s = 100$)

Algorithm type	Infection rate	Error rate[%]		
		Max	Min	Ave
GAVI	0.02	11.048	1.542	5.109
	0.05	8.484	1.478	3.497
	0.10	6.861	0.250	2.389
	0.20	2.447	0.000	1.122
	0.30	2.432	0.000	0.871
	0.40	3.867	0.250	1.652
	0.50	6.822	0.250	2.639

Table 3: The result of GAVI for at 48 cities ($s = 50$)

Algorithm type	Infection rate	Error rate[%]		
		Max	Min	Ave
GAVI	0.02	16.038	2.193	5.548
	0.05	3.328	0.250	1.700
	0.10	7.846	0.000	1.839
	0.20	4.036	0.000	1.656
	0.30	3.443	0.798	1.372
	0.40	2.921	0.530	1.183
	0.50	4.979	0.530	2.130

5. Conclusions

We proposed GAVI for TSP and compared the performance of GAVI and GA to lead approximate solutions. From the simulations, the result of GAVI was better than GA by using appropriate *infection rate*. It was efficient that not only GA but also *Infection* applied in TSP. GAVI was valuable in convergence of the solution. We confirmed that VTE is efficient in TSP.

In future work, we would like to study the mechanism of *Infection* in detail. In this study, all number of element in *Infection* is depended on fixed probability. However, changing fixed probability each number of element would expect efficient. Moreover, it is necessary that consideration of diversity of genetics. We would expect to consideration of diversity of genetics in using Virus Infection algorithm obtains good solution in other TSP.

Acknowledgment

This work was partly supported by JSPS Grant-in-Aid for Young Scientists 23700269.

References

- [1] Little J, Murty K, Sweeney D, Karel C, “An algorithm for the traveling salesman problem,” Operations Research 11:972-89, 1963.

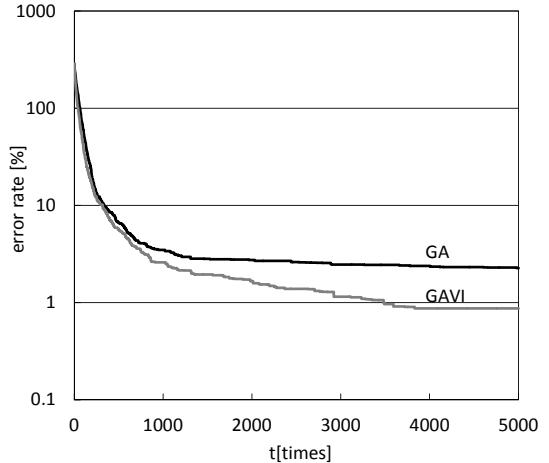


Figure 5: Error curves of GA and GAVI.

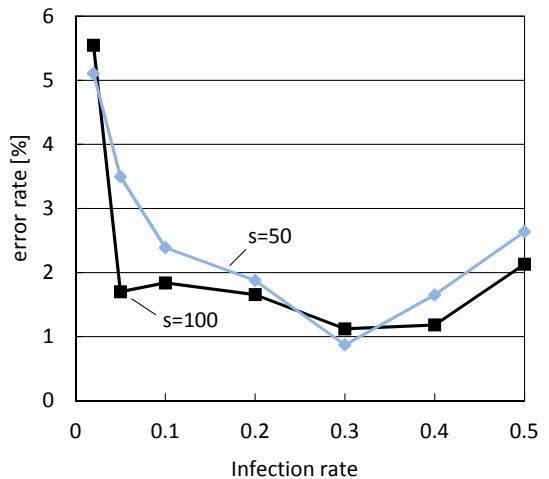


Figure 6: Relationship between *infection rate* and *error rate*.

- [2] Jean-Yves Potvin, “Genetic algorithms for the traveling salesman problem,” Annals of Operations Research 63, pp.339-370, 1996.
- [3] Kitano H ed., “Identeki Algorithm[Genetic Algorithm],” 1st ed.Sangyo Tosyo Kabushiki Kaisya, 1993.
- [4] Fang G, Hongwei L, Qiang Z, Gang C, “A Genetic Algorithm with a Mixed Region Search for the Asymmetric Traveling Salesman Problem,” Computers and Operations Research 30(5), 773-786, 2003.
- [5] Naoshi N, Akinori K and Kunio K, “An Evolutionary Algorithm Based on the Virus Theory of Evolution,” Information Processing Society of Japan Vol.40, No.5, 1999.
- [6] Gao F, Liu H, Zhao Q, Cui G, “Virus-evolutionary particle swarm optimization algorithm,” vol 4222. Springer, Berlin, pp 156-165, 2006
- [7] Hideomi N, Takashi S and Takashi F, “Virus theory of evolution,” Bulletin of Yamanashi Medical University Vol.3, pp.14-18, 1986.
- [8] Zhaxybayeva O, Doolittle W F, “Lateral gene transfer,” Curr. Biol. 21, R242-246 2011