Effectiveness of Combination of Immune Algorithm and Virus Theory of Evolution for QAPs

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***Abstract*— This paper presents the solving method of Quadratic Assignment Problems (QAPs). This method uses both Artificial Immune System (AIS) and Virus Theory of Evolution (VTE), and we call it Evolutionary Algorithm with Immune and Infection (EAII). EAII has characteristics of both AIS and VTE. We consider that EAII is effective method for QAPs. Thus, we apply EAII to the QAPs and confirm that EAII obtains more effective result than IA. Furthermore, we analyze the reason for obtaining better solution in EAII.**

I. Introduction

Optimization problem is the problem to analyze state of maximum or minimum value in the function of a specific set. Some optimization problems are difficult to find the optimum solution. For example, these problems are Function Optimization Problem, Traveling Salesman problem, Knapsack Problem and so on. Quadratic Assignment Problem (QAP) [1],[2] is known as one of difficult problems to find the optimum solution.

Artificial Immune System (AIS) [3] is computer system based on immune system of living organisms. AIS is able to apply to a variety of fields [4]-[6]; optimization problems, pattern recognition, robotics and so on. Immune Algorithm (IA) [7]-[9] is based on AIS and is devised in immune system of possessing organisms. IA finds optimal solution by updating antibody group.

In this study, we focus attention on infection algorithm. The infection algorithm is based on Virus Theory of Evolution (VTE) [10]-[12], Characteristic of VTE seems to be useful for finding the approximate solution quickly. If we propose the algorithm to use both infection algorithm and immune system, we can make a prediction that this algorithm obtains better result than IA. Thus, we propose Evolutionary Algorithm with Immune and Infection (EAII). EAII is the hybrid method of infection algorithm and IA. We confirmed effectiveness of EAII in [13]. In this paper, we investigate more detailed effectiveness of EAII.

II. Quadratic Assignment Problem

The Quadratic Assignment Problem (QAP) [1],[2] is demanded looking for the best allocation of activities in locations. Task of the QAP is to assign all activities to different locations with the minimum cost among all combinations. The QAP has two matrices (F and D) of the dimension $n \times n$ (n indicates the size of problems). The matrix of F indicates each flow of activity, and the matrix of D indicates each distance. In using F and D, total assignment cost $E(P)$ is shown as Eq. (1).

$$E(P) = \sum_{i=1}^{n} \sum_{j=1}^{n} f_{ij} d_{p(i)p(j)} \tag{1}$$

where f_{ij} and $d_{p(i)p(j)}$ are (i,j)-th elements of D and F, $p(i)p(j)$ is a alignment value.

For example, the matrix of F and D are defined by Eqs. (2) and (3). Figures 1 and 2 can indicate Eqs. (2) and (3). If f of flow allocate $P(f2,\ f1,\ f4,\ f3)$ to $(d1,\ d2,\ d3,\ d4)$, calculation result of $E(P)$ is shown as Eq. (4).

$$F = \begin{bmatrix} 0 & 5 & 10 & 2 \\ 5 & 0 & 6 & 3 \\ 10 & 6 & 0 & 4 \\ 2 & 3 & 4 & 0 \end{bmatrix} \tag{2}$$

$$D = \begin{bmatrix} 0 & 21 & 11 & 44 \\ 21 & 0 & 12 & 30 \\ 11 & 12 & 0 & 9 \\ 44 & 30 & 9 & 0 \end{bmatrix} \tag{3}$$

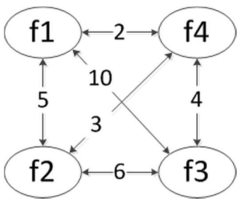

Fig. 1: Flow of activity.

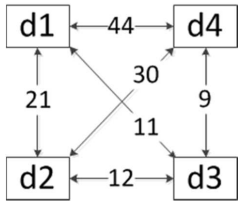

Fig. 2: Distance.

$$\begin{aligned} E(P) &= \sum_{i=1}^{4} \sum_{j=1}^{4} f_{ij} d_{p(i)p(j)} \\ &= \begin{bmatrix} 0 & 5 & 10 & 2 \\ 5 & 0 & 6 & 3 \\ 10 & 6 & 0 & 4 \\ 2 & 3 & 4 & 0 \end{bmatrix} \begin{bmatrix} 0 & 21 & 30 & 12 \\ 21 & 0 & 44 & 11 \\ 30 & 44 & 0 & 9 \\ 12 & 11 & 9 & 0 \end{bmatrix} \\ &= 1524 \end{aligned} \tag{4}$$

If the size of n increases, the total combination of allocation explodes. The task of QAP is to demand minimum value of $E(P)$.

III. Virus Theory of Evolution

Organic evolution is theory based on natural selection. In natural world, individuals of high fitness survive, while individuals of low fitness organism become extinct. Over the years, only higher fitness individuals survive. We call it Evolution. Thus, evolution needs to overlay generations. 6 On the other hand, Virus Theory of Evolution (VTE) [10] has proposed aside from organic evolution. This theory is based on the evolution by Lateral Gene Transfer (LGT) [11] in Virus infection. LGT is uptake of the gene to 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. Algorithms of using VTE was proposed in the past [12]. We assume using VTE algorithm leads the approximate solution in less time and VTE theory is efficient for the QAP.

IV. Evolutionary Algorithm with Immune and Infection

Evolutionary Algorithm with Immune and Infection (EAII) is based on AIS [7],[8] and VTE. Flow chart of EAII is shown in Fig. 3. Flow of EAII shows Steps1-5. Step2 from Step5 is repeated until the set iteration (t_{max}).

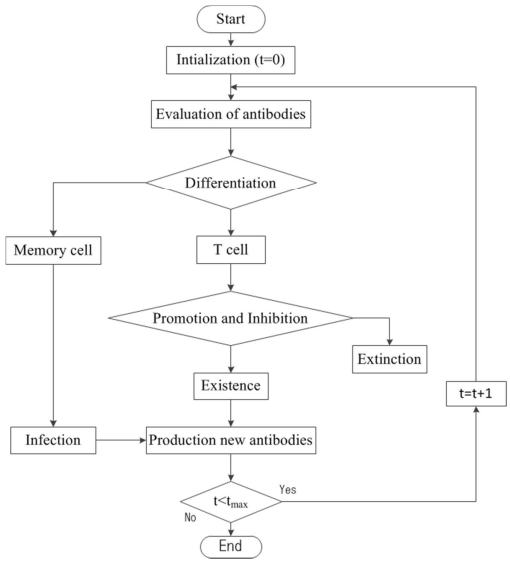

Fig. 3: Flow chart of EAII.

Step1 Initialization

We prepare a number of random location selection. We define the number of random locations as antibodies. The number of random locations selection is U.

Step2 Evaluation of antibodies

Level of affinity: Level of affinity indicates evaluation value, and is defined by the following Eq. (5).

$$\phi_v = \frac{1}{E(v)} \tag{5}$$

Degree of similarity: Degree of similarity of antibody v and w is defined by the following Eq. (6).

$$\Psi_{vw} = \frac{1}{1 + H_{vw}} \tag{6}$$

H_{vw} indicates hamming distance of v and w. Thus, when v and w are exactly the same, H_{vw} equals 0.

Concentration: Concentration is defined by the following Eq. (7),(8). (U: Number of antibodies)

$$\Theta_v = \frac{1}{U} \sum_{w=1}^{U} \pi_{vw} \tag{7}$$

$$\pi_{vw} = \begin{cases} 1 \ (\Psi_{vw} \geqq T_1) \\ 0 \ (\Psi_{vw} < T_1) \end{cases} \tag{8}$$

When Ψ_{vw} cross threshold of T_1, π_{vw} reflects Θ_v.

Step3 Differentiation

Memory cell: This section is differentiation of antibodies into memory cell. If concentration Θ_v of each antibody v cross threshold of T_2, v changes candidate memory cell μ. When μ do not reach a upper limit of number of memory cells, μ becomes differentiated into memory cell. While μ reach a upper limit of number of memory cells, we calculate degree of similarity $\Psi_{\mu m}$ of μ and m. When evaluation value of μ cross highest value of $\Psi_{\mu m}$, μ becomes differentiated into memory cell.

T cell: This sections differentiation of antibodies into T cell. v becomes differentiated into T cell t in descending order of concentration. We calculate degree of similarity Ψ_{vt} of v and t. If Ψ_{vt} cross threshold of T_3, v become extinct. This behavior indicates inhibition of similar solution. Extinct antibodies replenish new antibodies by random number.

Step4 Promotion and Inhibition of production antibodies

Extinction and existence: We calculate level of affinity ϕ_v by all antibodies v. Number of $\frac{N}{2}$ of v exist in descending order of ϕ_v. While, other $\frac{N}{2}$ of v become extinct.

Production new antibodies: In surviving antibodies v, new antibodies are produced by Crossover. Crossover is to be mated the two locations like Fig. 4.

Step5 Infection

We select one memory cell. New antibodies are infected by a part of element of selected memory cell. Selected memory cell changes each time, and the selected number of element is decided with fixed probability. Part of antibody changes the information held like Fig. 5. We call it *Infection*. In this study, we define *Infection rate*. *Infection rate* indicates a fraction that antibodies group acquire the *Infection*.

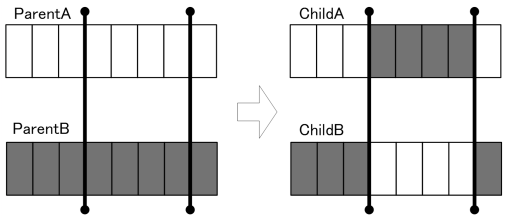

Fig. 4: The mechanism of *Crossover*.

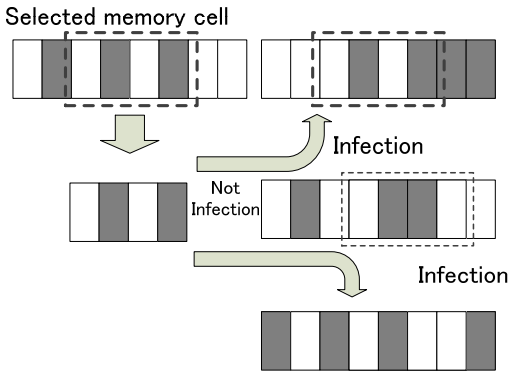

Fig. 5: The mechanism of *Infection*.

V. Simulation Results

In order to compare the performance of EAII and IA, we apply to find approximate solutions in QAPs. In this study, the number of t_{max} is 5000 times, the number of simulation is 100 times, U is 2048, applying QAP type are 5 kinds [2]. *error rate* is defined by the following Eq. (9).

$$Error\ rate[\%] = \frac{(obtain) - (optimum)}{(optimum)} \times 100 \qquad (9)$$

where *obtain* denotes obtained solution and *optimum* shows optimum solution. When *obtain* value approaches *optimum* value, *Error rate* is low.

Tables I shows result of EAII and IA. IA is same the number of t and U for comparing performance of EAII. Infection rate in EAII is 20%. We use these parameters of the each best result by simulation results and average value in 100 times. In results of Table I, we confirm that EAII obtains the better solution than IA.

TABLE I: The result of *Error rate*[%]

QAP type	Size	IA	**EAII**
tai12a	12	3.17	**0.86**
scr12	12	2.35	**0.06**
nug20	20	8.26	**3.59**
had20	20	2.62	**1.07**
nug30	30	14.69	**9.28**

Next, we investigate distribution of solutions by nug20, had20 and nug30 (t_{max} = 5000, U = 2000). Figures 6-8 show sort solutions by low cost of $E(P)$ in antibodies. Horizontal axis is sort solutions by low cost of $E(P)$ in antibodies, and vertical axis is the cost of $E(P)$. Initialization of EAII and IA are same configuration. EAII obtains wider range of $E(P)$ than IA in Figs. 6-8. Namely, we consider that EAII obtains more diverse solution than IA. Because, it is necessity to keep diverse solutions for escaping local minimum. Thus, the result of EAII is better than IA.

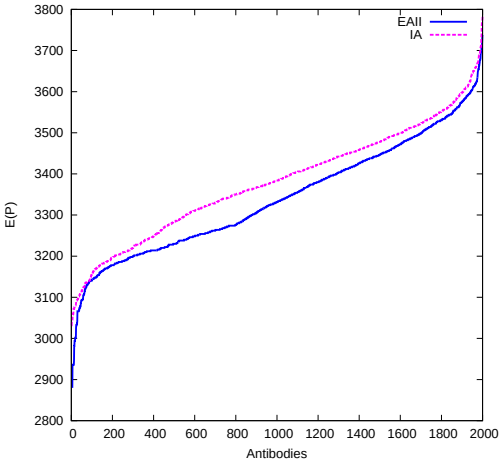

Fig. 6: Distribution of solution in nug20.

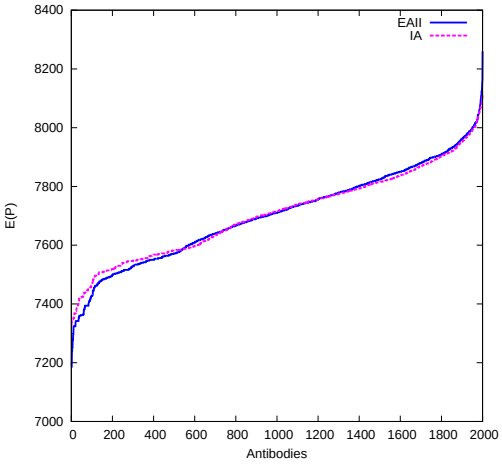

Fig. 7: Distribution of solution in had20.

Finally, we investigate evaluation value by changing the number of memory cell in EAII. The number of memory cell is changed from 1 to 40, the number of simulation is 30 times, each value uses average value by 30 times. (t_{max} = 5000, U = 2048). Figures 9-11 show relationship between the number of memory cell and evaluation value. Horizontal axis is the number of memory cell, and vertical axis is the cost of $E(P)$. The number of memory cell increases, EAII does not obtain good solution. Thus, we need to set the appropriate the number of memory cell.

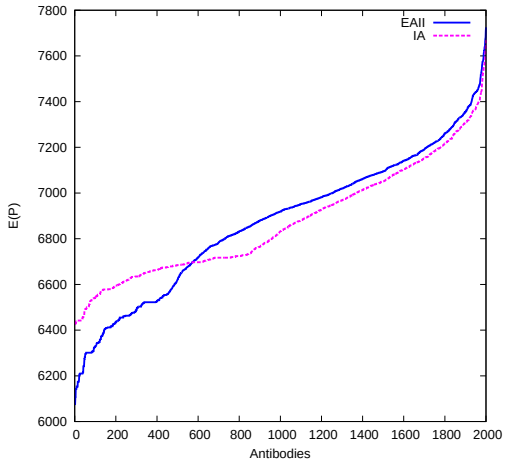

Fig. 8: Distribution of solution in nug30.

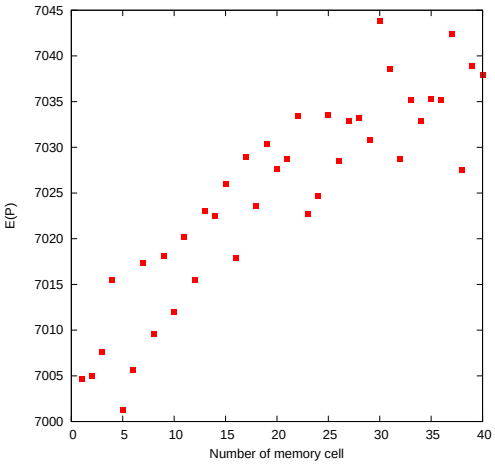

Fig. 10: Changing memory cell in had20.

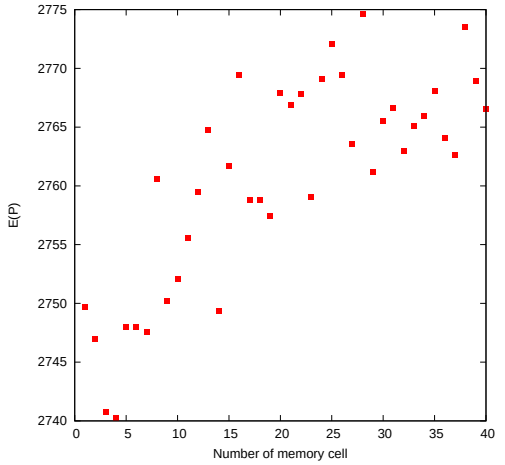

Fig. 9: Changing memory cell in nug20.

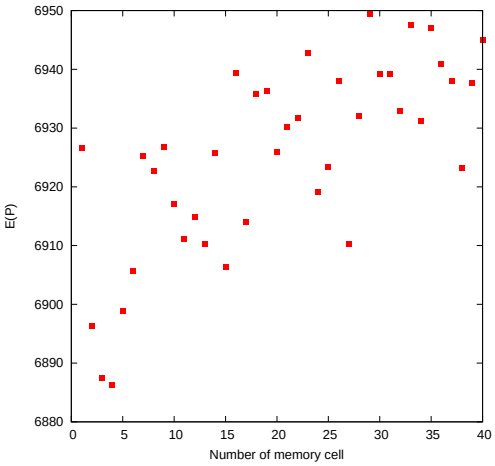

Fig. 11: Changing memory cell in nug30.

VI. Conclusions

We proposed EAII for solving the QAP, and compared the performance of EAII and IA to lead approximate solutions. From the result, the result of EAII was better result than IA. EAII obtained all kinds of evaluation value, and it is important to keep of diverse solution in solving solution of the QAP. Thus, it was efficient to use VTE based on IA in the QAP. We expect that apply these results to technological application possibility. In future work, we would like to study the mechanism of *Infection* in detail. We expect to obtain a better solution by studying mechanism of *Infection*.

References

[1] E. Lawler, "*The Quadratic Assignment Problem,*" Management Science 9, pp.586 1963.

[2] R.E. Burkard, S.E. Karisch, F. Rendl, "*QAPLIB - A Quadratic Assignment Problem Library,*" Journal of Global Optimization Volume 10, Issue 4, pp.391-403, 1997.

[3] de Castro L., Von Zuben F., *"Artificial Immune System: Part I - Basic Theory and Applications,"* Technical Report, TR-DCA, 1999.

[4] de Castro L., Von Zuben F., *"Artificial Immune System: Part II - A Survey of Applications,"* Technical Report, TR-DCA, 1999.

[5] S. Garrett, *"How Do We Evaluate Artificial Immune Systems?,"* Evolutionary Computation, vol.13, no.2, pp.145-178, 2005.

[6] D. Dasgupta, S. Yu, F. Nino, *"Recent advances in artificial immune systems,"* Applied Soft Computing, 11(2), pp.1574-1587, 2011.

[7] K. Mori and M. Tsukiyama, *"Immune algorithm with searching diversity and its application to resource allocation problem,"* Transactions on JIEE 113-C (10), 1993.

[8] K. Mori , M. Tsukiyama and T Fukuda *"Application of an immune algorithm to multi-optimization problems,"* T. IEEE Japan, vol.117-C, no.5, pp.593 -598 1997.

[9] V. Cutello, G. Nicosia, M. Pavone, J. Timmis, *"An Immune Algorithm for Protein Structure Prediction on Lattice Models,"* IEEE Transactions on Evolutionary Computation, vol.11, no.1, pp.101-117, 2007. 86.

[10] Domingo E, Escarmis C, Sevilla N, Moya A, Elena SF, et al, *"Basic concepts in RNA virus evolution.,"* FASEBJ, 10: 859-64, 1996.

[11] Zhaxybayeva O, Doolittle W F, *"Lateral gene transfer,"* Curr. Biol. 21, R242-246, 2011.

[12] N. Nakayama, A. Kanasugi and K. Kondo, *"An Evolutionary Algorithm Based on the Virus Theory of Evolution,"* Transactions of Information Processing Society of Japan, Vol.40, No.5 p2346-2355, 1999.

[13] T. Inoue, Y. Uwate and Y. Nishio "*Effectiveness of Combination of Artificial Immune System and Virus Theory of Evolution for QAPs,*" Proceedings of International Symposium on Nonlinear Theory and its Applications (NOLTA'14), pp.160-163, 2014.