2011 International Symposium on Nonlinear Theory and its Applications
NOLTA2011, Kobe, Japan, September 4-7, 2011

Performance Enhancement of Amoeba-based Neurocomputer for 8-City Traveling Salesman Problem

Masashi Aono†, Liping Zhu‡, Song-Ju Kim†, Masahiko Hara†‡

†Flucto-Order Functions Research Team, RIKEN-HYU Collaboration Research Center,
RIKEN Advanced Science Institute, Japan
‡Tokyo Tech-RIKEN International School, Tokyo Institute of Technology, Japan
Email: masashi.aono@riken.jp

Abstract—Many biological organisms manage a trade-off between the accuracy and speed of their decision making that are conflicted objectives for surviving in uncertain environments. A single-celled amoeboid organism, the true slime mold *Physarum polycephalum*, exhibits rich spatiotemporal oscillatory dynamics and sophisticated resource allocation capabilities. To evaluate the accuracy and speed of the resource allocation, previously the authors constructed an experimental computing system that leads the organism to search for a solution to the 8-city Traveling Salesman Problem (TSP). With the assistance of optical feedback to implement a recurrent neural network model, the organism changes its shape by alternately expanding and shrinking its photosensitive branches so that its body area can be maximized and the risk of being illuminated can be minimized. The system found a high quality TSP solution (i.e., a relatively shorter route) with a high accuracy. In this study, we show that, with changes in the experimental condition of the optical feedback system, the speed at which the system searches for the solution was enhanced significantly without degrading the accuracy. Counterintuitively, to speed up the search process, the organism acquired less information from the optical feedback compared with our previously performed experiments. These findings suggest that the search dynamics of the organism may be tuned to become "economical" to get a high quality solution at lower exploration cost.

1. Introduction

A plasmodium of the true slime mold *Physarum polycephalum* (Fig. 1A) is an amoeboid multi-nucleated unicellular organism that has been studied actively to explore its capabilities of decentralized computing. Nakagaki demonstrated that the organism is capable of connecting the optimal routes among foods [1].

When the organism is placed in a multi-lane stellate chip resting on an agar plate (Fig. 1B), it elongates its branches in the lanes of the chip and changes its shape by expanding or shrinking the branches at each period (1 to 2 min) of autonomous oscillation. These complex oscillatory movements allocate the intracellular resources to the branches and are used as search dynamics in our context.

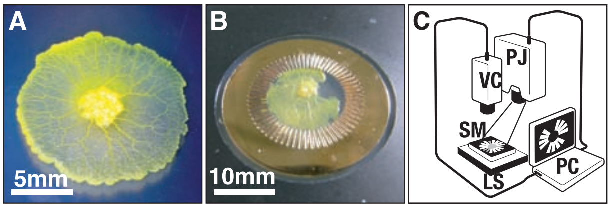

Figure 1: (A) An amoeboid organism *P. polycephalum*. (B) An Au-coated plastic chip resting on a nutrient-rich agar plate. The organism remains inside the chip where the agar is exposed because of its aversion to metal. (C) Experimental setup. For transmitted light imaging using a video camera (VC), the sample organism and chip (SM) were illuminated from beneath with a surface light source (LS). The recorded image was processed using a PC to update the grayscale image pattern for illumination with a projector (PJ).

The organism withdraws its branch when illuminated by visible light. This negative phototactic behavior enables us to make the organism withdraw its branches from illuminated lanes, and grow toward non-illuminated lanes. Thus, when we project an image pattern[1] using a commercial PC projector, we can lead the organism to change its shape as instructed by the illumination pattern.

By introducing an optical feedback system (Fig. 1C), the authors created a biocomputer that employs the organism as a solution searcher for various combinatorial optimization problems. With changes in the shape of the organism, the system automatically updates the illumination pattern in accordance with a recurrent neural network algorithm [2, 3].

In our previous work [4], we demonstrated that our system is capable of finding a good solution to the 8-city TSP with a high probability. The experimental condition used in the previous work is referred to as "condition A" hereafter. In this study, to improve the circular symmetry of light stimulations, we perform the experiment in an alternative condition called "B," where we employ a new pro-

[1]The monochrome image gives an illumination pattern which represents illuminated and non-illuminated lanes with white and black rectangular regions, respectively.

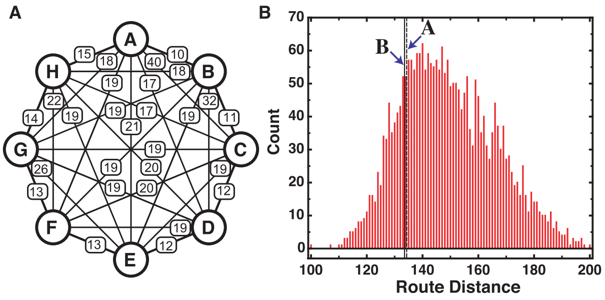

Figure 2: (A) A topological map of the 8-city TSP used in the experiments. (B) Distribution of solutions (valid routes) as a function of the route distance. The uniquely existed shortest and longest routes have the total distances 100 and 200, respectively. The solid and broken lines indicate the averaged scores of the results obtained in experimental conditions A and B, respectively.

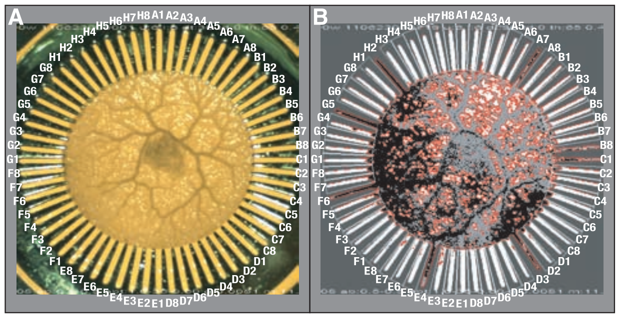

Figure 3: (A) The initial configuration. (B) A valid solution *CHDEGFAB* with the route distance 128. Black and gray pixels represents that the thickness of the corresponding region of the organism was increased and decreased, respectively. Red pixels show the border between the body of the organism and unoccupied agar region (white pixels). White trapezoids indicate the illuminated regions.

jector that is different from the one used in condition A. Using the same map shown in Fig. 2A, we compare the performances of our system in the two conditions. We show that the changes in the external experimental environments lead the intrinsic dynamics of the organism to search for a solution in a more economical manner.

2. Methods

2.1. Amoeba-based Neurocomputing

According to the recurrent neural network model proposed by Hopfield and Tank [5], the N-city TSP can be solved with $N \times N$ neurons. To implement the 8-city TSP solution, we use 64-lane chip (Fig. 1B) put on a nutrient-rich agar plate. As shown in Fig. 3, each lane of the chip is labeled with $i \in \{Pn \mid P \in \{A, B, \cdots, H\}, n \in \{1, 2, \cdots, 8\}\}$ indicating the city name P and its visiting order n. When the organism sufficiently elongates its branch in lane Pn, we consider that city P was visited nth.

For each i at time t, the state $x_i(t) \in [0.0, 1.0]$ is defined as the fraction of the area occupied by the branch of the organism inside the corresponding lane (i.e., x_i = the area of branch i / the area of the entire region of lane i) and is obtained by digital image processing.

When the light illumination $y_i(t) \in [0.0, 1.0]$ for lane i is applied with the maximum luminous intensity, we write this status as $y_i = 1.0$, whereas $y_i = 0.0$ denotes that the illumination is completely turned off.

Each branch of the organism inherently grows and tends to occupy the entire region of the corresponding lane in principle when $y_i = 0$. Namely, if no illuminations were applied, all 64 branches would fully elongate to fill the entire region in the chip. Due to the photoavoidance behavior of the organism, illuminating lane i as $y_i > 0$, we can inhibit the long-term increase in the state x_i. When x_i is large, the long-term decrease in x_i can be promoted by the illumination $y_i > 0$.

The optical feedback system automatically updates each illumination status y_i at every interval of $\Delta t = 6$ sec in accordance with the following neural network dynamics.

$$y_i(t + \Delta t) = 1 - S(\textstyle\sum_j w_{ij} \cdot s(x_j(t))), \tag{1}$$

$$S(x) = 1/(1 + \exp(-B \cdot (x - \Theta))), \tag{2}$$

$$s(x) = 1/(1 + \exp(-b \cdot (x - \theta))), \tag{3}$$

$$w_{ij} = \begin{cases} -\alpha & (\text{if } i = Pn \ \wedge \ j = Pm \ \wedge \ n \neq m), \\ -\beta & (\text{if } i = Pn \ \wedge \ j = Qn \ \wedge \ P \neq Q), \\ -\gamma \cdot dst(P, Q) & (\text{if } i = Pn \ \wedge \ j = Qm \ \wedge \ P \neq Q \\ & \quad \wedge \ |n - m| = 1), \\ 0 & (\text{otherwise}). \end{cases} \tag{4}$$

We introduced the sigmoid function s so that we can adjust the sensitivity of the optical feedback system to the movements of the organism, where the experiments were carried out with a steepness parameter $b = 35$ and a threshold adjustor $\theta = 0.6$. Another sigmoid function S was defined with $B = 1000$ and $\Theta = -0.5$.

The inhibitory coupling weight $w_{ij}(= w_{ji} < 0)$ creates an exclusive relationship between the branches i and j in which the increase of x_j results in the decrease of x_i, and vice versa. The weight is determined by Eq. (4) to impose the following three aspects of the TSP solution; 1) prohibition of revisiting a once-visited city; 2) prohibition of simultaneous visits to multiple cities; and 3) reflection of a travel distance between two cities. The regulations of 1), 2), and 3) are tightened by the three parameters that we set in the experiments as $\alpha = 0.5$, $\beta = 0.5$, and $\gamma = 0.0081$[2], respectively.

[2] γ should be set as large as possible, so that differences in route distances can be maximally reflected in the optical feedback dynamics. However, γ has to be smaller than $\gamma^\star$ defined as follows: $\gamma^\star = \Theta/(dst(P^\star, Q^\star) + dst(Q^\star, R^\star))$, where city $Q^\star$ has the two longest edges connected with cities $P^\star$ and $R^\star$. I.e., $\{P^\star, Q^\star, R^\star\} = argmax_{\{P,Q,R\}}(dst(P, Q) + dst(Q, R))$. For the map shown in Fig. 2A, we can numerically obtain $\gamma^\star \simeq 0.00819672 > \gamma = 0.0081$.

	Projector Light Intensity ($\mu W/mm^2$)	Video Camera Resolution ($pxl \times pxl$)
A	652	320×240
B	352	640×480

Table 1: Equipment specs of conditions A and B.

Owing to the regulation 3), two branches trying to select a longer edge are more frequently illuminated than other branches selecting a shorter edge. This is because the former branches cause other conflicting lanes to have lower threshold values so that the conflicting branches can easily evoke the illuminations even by their slight growth movements. Due to this lower tolerance for perturbations, a longer solution is less stable than a shorter solution. Therefore, an optimal solution (i.e., the shortest route) is considered to be the most stable among all solutions. It allows the organism to relax maximally by maximizing its body area while minimizing the potential risk of being illuminated.

2.2. Experimental Conditions A and B

Major differences between the experimental conditions A and B are that we used different projectors and video cameras. The projector of condition B (W6000, BenQ [2500 lm, contrast ratio 5000 : 1]) enhanced the circular symmetry of light stimulations compared with that of condition A (U5-732h, PLUS Vision Corp. [2500 lm, contrast ratio 2000 : 1]), as the former can shift the optical angle arbitrarily while the latter cannot. However, as shown in Table 1, the light intensity of the former was much lower than that of the latter, where we measured a white pattern (R:G:B=255:255:255) using a power meter (Power/Energy Meter Model 1825-C, NEWPORT). The resolution of the video camera of the former (ARTCAM-036MI, ARTRAY) was higher than that of the latter (CCD IRIS, SONY).

Other experimental parameters of conditions A and B were equalized as follows. The dimensions of the multilane chip made from an ultrathick photoresist resin (SU-8 3050, MICROCHEM Corp.): Thickness approx. 0.1 mm, diameter 23.5 mm, diameter of the center disk 12.5 mm, and each lane 0.45×3 mm. The top and bottom surfaces of the chip were coated with Au using a magnetron sputterer (MSP-10, Shinkuu Device Co., Ltd.). Ingredients of a nutrient-rich agar plate were: Ultrapure water (Milli-Q) 100 ml, BactoAgar 1.5 g, Glucose 0.36 g, KCl 0.074 g, MaltExtract 1 g, and Peptone 0.1333 g. We added Hemin solution 0.5 ml to these ingredients after autoclave sterilization (120°C, 20 min), where the Hemin solution contained Hemin 25 mg and NaOH 1 g diluted with ultrapure water 50 ml. The surface of the plate was covered with a plastic sheet to avoid moisture evaporation, which causes drawdown of altitude of the chip.

The experiments were conducted in a dark thermostat and humidistat chamber (27 ± 0.3°C, relative humidity 96±1%, THG102FB, Advantec Toyo Kaisha, Ltd.). For transmitted light imaging, the sample was placed on a surface light guide (MM80-1500, Suruga Seiki Co., Ltd.) connected to a halogen lamp light source (TECHNO LIGHT KTX-100R, Kenko Co., Ltd.) equipped with a band-pass filter (46159-F, Edmund Optics Inc.), which was illuminated with light (intensity 2 μW/mm^2) at a wavelength of 600±10 nm, under which no influence on the behavior of the organism was reported. The outer edge of the chip (the border between the chip and the agar region) was always illuminated using the projector to prevent the organism from moving beyond the edge. The program codes for realtime image processing for optical feedback were written in Visual C++ using a commercial developer studio (Visual Studio, Microsoft).

2.3. Computing Process

The initial configuration should be set as close to $x_i(0) = 0$ (for all i) as possible, so that the organism can examine the illumination patterns as many as possible. Therefore, illuminating all the lanes in the chip, we waited until the center disk of the chip was fully covered with the body of the organism (average 14 ± 3 mg), as shown in Fig. 3A.

The organism exhibited various spatiotemporal oscillation patterns, such as concentric, rotational, and chaotic wave propagations, and spontaneously switched among these patterns. The complex spatiotemporal dynamics produce fluctuated growth movements of the branches that evoked a variety of illumination patterns. Through this trial-and-error process, less frequently illuminated 8 branches elongated exclusively, and the system finally reached a valid solution as shown in Fig. 3B. We judged that the system reached the solution when the illumination pattern was kept unchanged for more than 10 min.

3. Results

3.1. Accuracy

We carried out 8 trials in condition A (reported in [4]) and 16 trials in condition B. The averaged results were summarized in Table 2. In condition A, the averaged route distance of the reached solution was 134.5 which is evaluated as "top 23%," i.e., the number of solutions shorter than 135 is 579 and is smaller than 23% of the number of all solutions ($2520 = (N-1)!/2$). This performance can be thought of as the accuracy of decision making of the system to reach a high quality solution. Although the top ranking (%) was improved in condition B, the improvement cannot be considered impressive because the averaged route distance 133.0 was not significantly better.

	Distance (Top %)	Time (min) to Reach	Patterns Explored	Patterns per min.
A	134.5 (23.0)	132.0	300.5	2.28
B	133.0 (18.7)	46.2	208.7	4.52

Table 2: Results obtained in conditions A and B.

3.2. Speed

As a measure of the speed of decision making, we evaluated the time required to reach a solution, which is the elapsed time since some of the lanes were first illuminated until the illumination pattern first represented a valid solution. It is noteworthy that the time to reach a valid solution in condition B was about three times better than that in condition A. The system was able to speed up the decision making without degrading the accuracy.

3.3. Information Exploration

To find a good solution, it is supposed that the organism needs to collect more information by exploring a wider variety of illumination patterns (i.e., grayscale images representing 64 On/Off states). We counted the variety of the patterns evoked in the course of solution search. As we excluded overlapping of identical patterns, the variety represents the extent of search space[3] explored by the organism.

As shown in Table 2, the number of patterns explored in condition B was rather smaller than that in condition A. That is, in condition B, the system achieved more speedy and accurate solution search by acquiring less information compared with condition A. The number of illumination patterns explored per unit time[4] increased in condition B. Namely, in condition B, the rate of information collection was higher but the accumulated amount of information was smaller.

4. Discussion and Conclusion

In this study, we showed that the changes in the external experimental environments activated the solution-searching ability of the organism. It is our future subject to clarify why the organism could become "smarter."

The search speed was enhanced without degrading the accuracy to find a high quality solution. Indeed, the rate of information collection became higher. However, the accumulated amount of information, which was counted as the number of illumination patterns explored, did not get higher but became rather smaller. This is inconsistent with a generally accepted belief that the system would find a good solution if it could explore a wider extent of search space for a longer time. Thus, the system might have taken an "economical" path to achieve the same quality of accurate solution search using lower exploration resources, such as shorter searching time and less information.

It would be hard to think that the system selects the economical path by a succession of "random" decision-making. Therefore, the economical search process might be considered as a series of correlated movements produced by the intrinsic dynamics of the organism. The authors have modeled the intrinsic dynamics of the organism and applied it to solving the "multi-armed bandit problem," a problem of managing the trade-off between the accuracy and speed of resource allocation in an economical manner [6, 7]. Our model was found to work better than other well-known algorithms for the problem. Further studies on the economical resource allocation will contribute to understanding and developing a wide variety of smart systems to make right decisions in uncertain environments.

[3] As we binarized the illumination status y_i into On and Off state, the number of all possible illumination patterns is 2^{64}, which represents the entire extent of the search space.

[4] The number of explored patterns was divided by the time to reach a valid solution.

Acknowledgments

This work was supported by KAKENHI (22700322). The authors thank Dr. Takashi Isoshima and Ms. Yuki Hasegawa (RIKEN) for their cooperation for experiments.

References

[1] T. Nakagaki, H. Yamada, A. Toth, "Maze-solving by an amoeboid organism," *Nature*, vol.407, pp.470, 2000.

[2] M. Aono, M. Hara, K. Aihara, "Amoeba-based neurocomputing with chaotic dynamics," *Communications of the ACM*, vol.50 (9), pp.69–72, 2007.

[3] M. Aono, Y. Hirata, M. Hara, K. Aihara, "Amoeba-based chaotic neurocomputing: combinatorial optimization by coupled biological oscillators," *New Generation Computing*, vol.27, pp.129–157, 2009.

[4] M. Aono, L. Zhu, M. Hara, "Amoeba-based Neurocomputing for 8-City Traveling Salesman Problem," *International Journal of Unconventional Computing*, to appear.

[5] J. J. Hopfield, D. W. Tank, "Computing with Neural Circuits: A model," *Science*, vol.233, pp.625–633, 1986.

[6] S.-J. Kim, M. Aono, M. Hara, " Tug-of-war model for multi-armed bandit problem," *In: Calude, C. (Ed.), Unconventional Computation. Lecture Notes in Computer Science*, Springer 6079, pp.69–80, 2010.

[7] S.-J. Kim, M. Aono, M. Hara, "Tug-of-war model for two-bandit problem: Nonlocally correlated parallel exploration via resource conservation," *BioSystems*, vol.101, pp.29–36, 2010.