Simulate Phototactic Behavior and Puddle-Crossing Behavior: Preparation for Assembly of Soldier Crabs' Swarm Logical Gates

Yuta Nishiyama[1†], Kyohei Sagawa[1], Hisashi Murakami[2], Claudio Feliciani[3], Davin Browner[4], and Andrew Adamatzky[4]

[1]Department of Information and Management Systems Engineering, Nagaoka University of Technology, Niigata, Japan
[2] Faculty of Information and Human Science, Kyoto Institute of Technology, Kyoto, Japan
[3] Department of Aeronautics and Astronautics, School of Engineering, The University of Tokyo, Tokyo, Japan
[4] Unconventional Computing Laboratory, University of the West of England, Bristol, UK
(Tel : +81-258-47-9376; E-mail: y-nishiyama@kjs.nagaokaut.ac.jp)

Abstract: Living organisms have been expected to realize an emergent computing. Although a wide variety of biological systems has been exploited as computing devices, there have been a few attempts of computing devices employing animal collective behaviors. The previous studies have implemented collision-based logical gates employing swarms of soldier crabs, *Mictyris guinotae*. However, how to control their movements in connected multiple gates has yet to be proposed. In this study, two kinds of their behaviors, a positive phototaxis and a puddle-crossing, were reproduced in the mutual anticipation model with an environmental factor. We discuss that utilizing these behaviors has a possibility to control crabs' flow in computing path to connect gates while maintaining their autonomy.

Keywords: Emergent computing, Collision-based logical gate, Soldier crab, Phototaxis, Emergent collective behavior

1. INTRODUCTION

Employing biological systems as computing devices is motivated by expectations for computation with evolutionary, adaptable, and even emergent properties [1]. Conventional computing systems process information in a certain frame that programmers/users define in isolation from the outside of it. Such systems would not evolve in and adapt to dynamically variable surroundings and never exhibit the emergent property. The notion of emergent property in computation is expressed as unpredictable global behavior arisen from local nonlinear dynamics [2], which appears when the global behaviors cannot be reduced into local behaviors. Therefore, living organisms are suitable for realization of emergent computing because they can maintain the unity as a whole while holding the discrepancy between global and local behaviors.

A wide variety of biological systems has been exploited as computing devices, e.g., slime mold; plant; fungi; proteinoid. Especially, the concept of the collision-based computing has inspired researchers to construct Boolean logic gates with living organisms instead of physical objects [3]. The original model of collision-based computer, also known as billiard ball computer [4], is based on collision between moving elastic balls, where presence or absence of balls at a certain place represent logical values 1 or 0, respectively. Likewise, but autonomously, slime mold logical gate works when two slimes are united or avoid each other while following the gradient of attractor [5]. Interestingly, although the slime mold gate operates with more or less 80% success rate, it can properly work even if a part of the gate is broken. This apparent robustness is realized by slimes changing their usual behavior. Authors argued that, because the discrepancy between uncontrollable behavior of slimes (local behavior) and computation of Boolean algebra (global behavior) is inherent in the gate, the slime mold gates are a robust machine in principle and have potential to emergent computing.

There have been a few attempts of computing devices employing animal collective behaviors although a lot of swarm intelligence algorithms have been proposed, e.g., ant colony optimization. The collective behavior of swarm, flock and school is often regarded as a self-organizing process so that the global pattern can arise spontaneously from interactions among members, where inherent noise causing the diversity of individual behaviors may play an essential role [6]. In this sense, animal collective behaviors also have the discrepancy between local and global behaviors and, therefore, would become a reasonable candidate to perform emergent computing.

The previous studies have implemented collision-based AND and OR gates employing swarms of soldier crabs, *Mictyris guinotae* [7 ,8]. This species is endemic to Ryukyu Islands, Japan, inhabiting intertidal or muddy sand substrate of inner bays and estuaries. It has a sub-spherical body and grows to approximately 15 mm of carapace length in males [9]. The crabs stay below the sand surface during high tides. During daytime low tides, large crabs appear on the surface, feed in droves on the waterlogged sand near the shoreline while walking forwards slowly, and generate swarms with internal turbulent flows. By contrast, during night-time low tides, they appear as well but feed individually and do not make swarms [10]. In the logical gate of soldier crabs, logical values 1 and 0 are given by a presence and absence of a swarm of them. The architecture shown in Fig. 1a constructs a two-input three-output Boolean logic gate $\langle x, y\rangle \rightarrow \langle \bar{x}y, xy, x\bar{y}\rangle$ using the mutual an-

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[†] Yuta Nishiyama is the presenter of this paper.

ticipation model described in the next section. If a swarm put on either input, it goes straight in a corridor. If swarms put on both inputs, they are united into one at the junction and it goes to the middle corridor because matching the moving directions among members. Importantly, a swarm having inherent noise (represented by $P = 20$ in Fig. 1b, also see in the next section) perform robust computing against an external noise. In general, logical gates are basic components of digital computer and can be used in combination. Considering soldier crabs moving in assembled gates just like electrons flowing through a wire in the electric circuits, finding how to control their movements would be useful for making a progress.

We focused on two characteristics related to the emergent behaviors of soldier crabs. One is a positive phototactic behavior. The real crabs self-organize better in response to the bright region in a dark environment [11]. The other is a puddle-crossing behavior. They collectively come into a puddle of water even though they individually do not enter it [12]. Both behaviors suggest that crabs' collective behavior can be tuned via environment. Although simulation study might predict assembly of soldier crabs' logical gates by utilizing the characteristic behaviors as connecting path, the previous studies have adopted different models to simulate them. In this study, we simulate both behaviors using the modified mutual anticipation model [13] in order to confirm possibilities of controlling crabs' movements with identical parameters.

2. MUTUAL ANTICIPATION MODEL

The mutual anticipation is explained as "reading each other's movements" in a nut shell. This capability cooperates with inherent noise to cause dynamical collective behaviors [13]. In a model, individuals have multiple potential transitions by which they can interact each other before moving. The mutual anticipation is implemented as the actual transition that is one of potential transitions selected via the interaction. The number of potential transitions results in inherent noise. Therefore, adjusting the impact of the potential transitions, especially values related to a popularity introduced below, would affect the global behaviors.

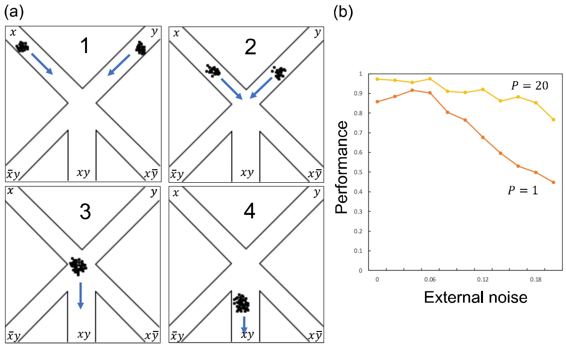

Fig. 1 Collision-based logical gate implemented by the mutual anticipation model [7]. (a) Snapshots of computing $\langle x, y\rangle \rightarrow \langle \bar{x}y, xy, x\bar{y}\rangle$ when $\langle x, y\rangle = \langle 1,1\rangle$. Time changes from 1 to 4. (b) Computing performance of the gate when $P = 1$ and $P = 20$.

The model in this study consists of N individuals moving in a continuous space as opposed to a discrete space that the original model introduced [12, 13]. The location of the k-th individual at the t-th step is given by $P(k,t) = (x, y)$, where $x, y \in \mathbb{R}$, $k \in K = \{1,2,\cdots,N\}$. Each individual has P number of potential vectors $v(k,t;i)$, $i \in I = \{0,1,\cdots,P-1\}$. When $i = 0$, the principal vector is expressed by the angle $\theta_{k,t}$, such that $v(k,t;0) = L\cos\theta_{k,t} + L\sin\theta_{k,t}$, where L shows the length of the principal vector. Otherwise, the potential vector is defined using a random value, η_i, selected with equal probability from [0.0, 1.0], and a random value (radian), ξ_i, selected with equal probability from $[-\alpha\pi, \alpha\pi]$, such that $v(k,t;i) = L\eta_i\cos(\theta_{k,t} + \xi_i) + L\eta_i\sin(\theta_{k,t} + \xi_i)$. Therefore, the principal vector, $v(k,t;\,0)$, is a special case where $\eta_i = 1.0$ and $\xi_i = 0.0$. For each $v(k,t;\,i)$, the target of the vector is represented by $\tau(k,t;i) = P(k,t) + v(k,t;i)$. To implement the mutual anticipation, the popularity of each target is calculated as the number of nearby targets within a radius R_p as following:

$$\zeta(k,t;i) = 1 + \left|\left\{\tau(k',t;i) \,\middle|\, \|\tau(k,t;i) - \tau(k',t;i)\| \le R_p, k' \in K \setminus \{k\}\right\}\right|.$$

The symbol $|S|$ represents the number of elements of a set S, and $\|x\|$ represents a length of a vector x.

The location of individuals is asynchronously updated between time steps t and $t+1$. At the beginning of the asynchronous update at t, a set U for recording the location of updated individuals is initialized as an empty set, φ, and the order of updating individuals is randomly determined by shuffling the sequence $(1,2,\cdots,N)$. The updating process of each individual begins with checking if there is an enough space around their targets because they cannot secure a spot with a radius R_o where somebody else occupies. This is represented by the popularity of zero, $\zeta(k,t;i) = 0$, when $(k' \in K \setminus \{k\})\|\tau(k,t;i) - P(k',t)\| \le R_o$. If there exists an $i\epsilon I$ such that $\zeta(k,t;i) \ge c$ $(c \in \mathbb{N}, c \ge 2)$, the present location for the k-th individual is recorded in the set U, such that $U = U \cup P(k,t)$, and then the next location is defined by

$$P(k,t) = \tau(k,t;s),$$

where s satisfies $\zeta(k,t;s) \ge \overset{\forall}{\square}(i\epsilon I)\zeta(k,t;i)$. The s-th target can reach the most popular place for the updating agent. If there are several most popular places, one of them is randomly chosen. This transition is the "mutual anticipation", which the individual moves to the target of its own potential vector that has the maximal popularity beyond the threshold value, c. The threshold value decides a difficulty to cause mutual anticipation, which is usually set to $c = 2$ for simulation of soldier crabs on a plane surface. Note that the next location is still expressed by $P(k,t)$ instead of $P(k,t+1)$ so that individuals yet to move can avoid places occupied by predecessors (see the above equation to check R_o).

If there is no $i\epsilon I$ such that $\zeta(k,t;i) \ge c$, the next location for the k-th individual is randomly chosen from places within the follower neighborhood, R_f, where updated individuals have gone. This transition is called "following", defined by

$$P(k,t) = Rd\{(x,y) \in U \mid \|P(k,t) - (x,y)\| \le R_f\},$$

where $Rd\{-\}$ is an operation to randomly choose an element from a set $\{-\}$. Note that a set U contains coordinates representing the place where updated individuals have previously occupied.

If the individual could perform neither the mutual anticipation nor following, it moves by

$$P(k,t) = Rd\{\tau(k,t;i) \mid 0 < \tau(k,t;i) < c\}.$$

This transition is called "free movement".

After all individuals have been updated, time step is finally updated as $(\forall k \in K) P(k,t+1) = P(k,t)$. It implies that t does not show a moment but a period of time in which all individuals are updated asynchronously. Moreover, the orientation of principal vectors is updated to be used at the next time step $t+1$. We implemented two separate ways to adjust the angle $\theta_{k,t}$. Velocity matching method adopts average direction of $v(k,t;0)$ within the neighborhood radius, M, around $P(k,t+1)$ as following: $\theta_{k,t+1} = \langle \theta_{k,t} \rangle_M$. Instead, movement history method is based on its own transition from t to $t+1$: $V(k,t) = P(k,t+1) - P(k,t)$. The angle $\theta_{k,t+1}$ is obtained as the angle of vector $q(k,t)$ defined by $q(k,t) = V_u(k,t) + w \cdot v_u(k,t;0)$, where x_u represents a unit vector of a vector x, and w is the weight of the previous principal vector.

3. SIMULATE CHARACTERISTIC BEHAVIOURS OF SOLDIER CRABS

3.1 Moving toward a stimulus of light

To simulate positive phototaxis of soldier crabs, we increased the value of popularity when the targets of the potential vectors reach to an affected area of light: $\zeta(k,t;i) = \zeta(k,t;i) + l \ (l \in \mathbb{N})$. We predicted that individuals would better stay at the affected area.

We carried out the simulation in a 500×500 space with a boundary condition given in a wrapped fashion, where parameters are $N = 20, P = 20, L = 30, \alpha = 0.8, R_o = 15, R_p = 7.5, R_f = 30$. The light-affected area was set up in the middle of the space as a circle with a radius $R_l = 30$. To compare effects of the additive value, l, we introduced five conditions: No-light, Uniform-low, Uniform-high, Gradient-low, Gradient-high (Fig. 2a). We let $l = 0$ in No-light condition, $l = 1$ in Uniform-low condition, and $l = 3$ in Uniform-high condition. In Gradient-low condition, the affected area had three zones with different values: $l = 3$ in $0 \le R_l \le 10$, $l = 2$ in $10 < R_l \le 20$, and $l = 1$ in $20 < R_l \le 30$. Likewise, Gradient-high condition gives $l = 5,4,3$ for each zone. In addition, we compared effects of two methods to adjust the principal vector: the velocity matching with $M = 30$ and the movement history with $w = 1$, as mentioned at the end of model section. We conducted 10 trials for each condition. A trial started with individuals randomly allocated in the space and lasted for 500 time-steps. We measured averaged population within the affected area.

Comparing between two methods to adjust the principal vector, we found that the movement history method kept more individuals in the affected area than the velocity matching method in all conditions except No-light condition (Fig. 2b). However, differences among conditions indicated a similar tendency in both methods: Gradient-high > Uniform-high > Gradient-low > Uniform-low > No-light.

3.2 Collectively crossing a puddle of water

The previous studies have demonstrated that puddle-crossing behavior is simulated by increasing the threshold value of popularity when the targets of potential vectors are in the puddle region [12]. We reproduce it by using the movement history method instead of the velocity matching that the previous studies used.

We carried out the simulation in a 300×900 closed space where a puddle area with $c = 3$, at the dimension of 300×300, was set up in the middle of the space and the other parts were land areas with $c = 2$ (Fig. 3a). We implemented individual's tendency to move along the boundary following the previous studies. All parameters except the number of individuals, N, were same as above-mentioned phototaxis simulation. We conducted 30 trials for each N. A trial started with N individuals randomly allocated in one of land areas and lasted for 200 time-steps. We obtained a proportion of individuals being in the other land area at the end of each trial. As a result, we found that the proportion increased with the number of individuals (Fig. 3b).

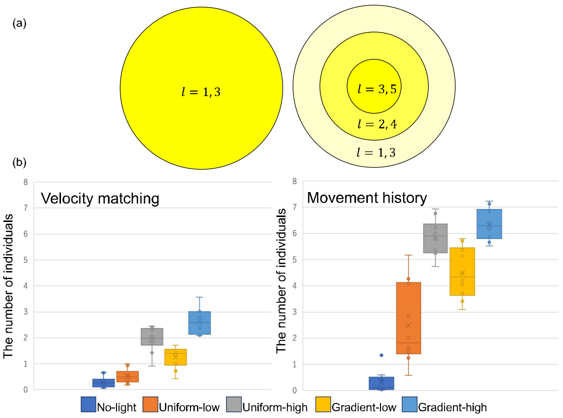

Fig. 2 Simulation of positive phototaxis. (a) Bright region expressed by an additive value, l, in uniform manner, left, and gradient manner, right. (b) The averaged number of individuals inside the bright region with velocity matching method, left, and movement history method, right.

4. DISCUSSION

This study investigated whether the mutual anticipation model simulate the phototactic behavior and the puddle-crossing behavior of soldier crabs using same parameters. We employed the model with a continuous

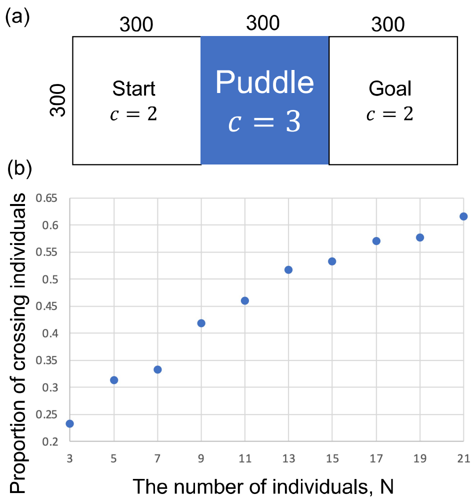

Fig. 3 Simulation of puddle-crossing. (a) Configuration of land areas and puddle area. (b) Proportion of individuals crossing the puddle.

space and adjusted values related to the popularity for introduction of external stimuli of light and water. Large value of popularity itself in a bright area made more individuals stay there although the configuration in the bright area did not have obvious influence. An increase of popularity threshold in a puddle area made proportion of individuals who crossed the area increase in a large size of group consistent with the previous study [12].

We focused on the popularity and its threshold to reproduce the characteristic behaviors. The popularity of the targets of potential vectors quantifies a likelihood that one is heading to the place where others are heading. Its size is determined by counting the number of others' targets near one's target. High popularity causes potential resonance among close individuals and leads them to a coherent and cohesive swarm. This inter-individual interaction was combined with an environmental factor of a light expressed by the additional value to the popularity in the bright area. In other words, the region of interaction was locally extended via an environment. Putting a spotlight on a specific region would allow us to control individuals to accumulate a swarm. In addition, similar parameter also reproduced the puddle-crossing behavior. This behavior occurs when enough individuals successfully accumulate near the edge of the puddle more than high popularity threshold [12]. Conversely, it is hard for a small number of individuals to cross the puddle until other individuals come to their neighborhood. This implies a maneuver to make them stuck before the puddle.

A provisional deadlock made of a puddle might be useful for adjusting the flow of crabs autonomously passing on a corridor between gates. Collision-based computing essentially requires well-defined positions and timing to observe interacting information carriers. However, we also should leave autonomous behaviors for crabs as long as expecting emergent properties that the they have. Use of a light and a puddle in combination might take advantage of both controllability and autonomy. For example, a dark region before a puddle would make crabs stuck and then spotlighting the edge of the puddle allows them to cross to the other side. Moreover, crossed individuals would be inhibited from returning to the original side unless they accumulate enough again, reminding us of a diode that transmits signals in one direction only. These suggest a possibility that we would be able to control their flow to some extent while maintaining their autonomy.

In this study, the mutual anticipation model reproduced the phototactic behavior and the puddle-crossing behavior of soldier crabs by adjusting effects of popularity as an environmental factor, suggesting use for balancing a control and an autonomy of their movements in paths to assemble the gates. Future works will investigate a global behavior when those emergent behaviors are implemented at the same time, where the contrast between a bright region and a dark region may be examined to effectively accumulate crabs at the edge of the puddle region. Moreover, assembling gates by utilizing those behaviors should be attempted practically to obtain more robust evidence. Then, group size would influence a definition of input/output and a success rate. In addition, other characteristic behaviors, e.g., digging to escape from threats, should be taken into consideration for comprehensive understanding of emergent computing potential.

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